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Individual, Family, and School Characteristics Associated with Academic Success Among Low-Income Students

Linda Kay Mayger
Lehigh University

Individual, Family, and School Characteristics Associated with Academic Success Among Low-Income Students

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Linda K. Mayger

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Date

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Craig Hochbein,
Dissertation Director
Assistant Professor of Education

____
Accepted Date

Committee Members:

____
George P. White
Professor of Education

____
Bridget V. Dever
Assistant Professor of School Psychology

____
Joseph J. Roy
Superintendent,
Bethlehem Area School District

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ABSTRACT

In light of the disproportionately small numbers of low-income students who obtain postsecondary degrees, the current study investigated the relationships between various characteristics of disadvantaged students and the level of K – 12 academic success that positioned them for postsecondary degree completion. After examining the literature related to academic resilience, the author found inconsistent identification of low-income students and low-level benchmarks for academic success. The lack of consistency in identifying low-income and academically successful students undermined the generalizability of the findings to students prepared for postsecondary education.

The purpose of the study was to determine (a) the level of cumulative proximal risk exposure associated with postsecondary degree completion; (b) the level of income associated with elevated proximal risk exposure; (c) the level of academic achievement associated with academically successful postsecondary degree completion; and (d) the individual, family, and school characteristics that were related to low-income students' academic success. The quantitative research design used samples from a national pool of 3,563 individuals from the Child Development Supplement of the Panel Study of Income Dynamics. Statistical analyses, involving a combination of logistic regression, multivariate analysis of variance, and discriminate analysis, yielded a number of important findings.

First, at a relatively low level of two direct risks, an individual's odds of postsecondary degree completion became unlikely. Second, the income level associated with elevated risk levels encompassed roughly the lower half of the CDS population. Third, individuals with mathematics achievement at or above the 70th percentile on the

Woodcock-Johnson were more likely to obtain postsecondary degrees. Fourth, the most significant and important characteristics associated with persistent academic success for low-income students, across school levels, were increased participation in extracurricular activities and high parental expectations for education. The findings had a number of implications for policy-makers, practitioners, and researchers interested in promoting the long-term academic success of low-income learners.

CHAPTER 1

Introduction

At every level of schooling, students from low-income families collectively perform at lower academic levels than their more advantaged peers (e.g., Hodgkinson, 2003; Institute for Higher Education Policy, 2010). Although each demographic level includes individual high- and low-achieving students, the substantial "difference in the average achievement of students from disadvantaged and middle class families" (Rothstein, 2008, pg. 8) results in a pervasive income achievement gap. Despite ample evidence that the income achievement gap carries societal ramifications, schools have failed to substantially increase the numbers of low-income, high-achieving students (National Science Board, 2010; OECD, 2014), thus the problem has persisted across generations as reduced education levels are a major cause of poverty and poverty places children at risk for educational failure (Arnold & Doctoroff, 2003). Consequently, the disproportionate representation of low-income students among the academically successful remains one of the most central problems in the field of education (Olszewski-Kubilius & Thompson, 2010, pg. 59).

Low-Income Children

At any given time, the income achievement gap negatively affects millions of American children. Disadvantaged children are dispersed through all geographic areas and racial and ethnic groups (Baldwin, 2007; Burney & Beilke, 2008). Although most cities contain substantial pockets of concentrated poverty, half of economically disadvantaged families live in rural locations (Addy & Wight, 2012). In 2013, the U.S. Census Bureau calculated that 20% of children under the age of 18 were living below the federal poverty line (DeNavas-Walt & Proctor, 2014). Likewise, 48% of public school students in Kindergarten through Grade 12 (K-12) qualified for the National School Lunch Program in 2010-11 because their families earned less than 185% of the federal poverty line (NCES, 2013b).

Table 1.
2012 Distribution of U.S. Children in Poverty

Racial or ethnic group	Number in millions
Hispanic	5.8
White	5.0
Black	3.9
Two or more races	0.7
Asian/Pacific Islander	0.5

Note. Adapted from (NCES, 2013a)

Not only is poverty distributed across ethnic groups, as shown in Table 1, children of color are overrepresented among the poor and, thus, disproportionally harmed by the income achievement gap (Abbott & Joireman, 2001; Hodgkinson, 1999; Orefield & Lee, 2005). These incongruent levels of representation point to variability in the ways people from various racial and ethnic groups experience the effects of poverty (Burney & Beilke, 2008; Coleman, 1966; Everson & Millsap, 2004; Orefield & Lee, 2005). Numerous researchers have investigated the complex interactions of race, ethnicity, and poverty on achievement and have concluded that poverty is the most important predictor of collective student performance (Abbott & Joireman, 2001; McLoyd, 1998; Alexander, Riordan, Fennessey, & Pallas, 1982; Entwisle & Alexander, 1993; Patterson, Kupersmidt, & Vaden, 1990; Peng & Wright, 1994). Consequently, while the racial achievement gap remains an important issue in education, the income achievement gap merits particular attention as a critical and related problem.

Preschool to High School Achievement Gaps

The negative effects of poverty begin to influence children's functioning in their earliest years, before they even enter school. Compared to more advantaged children, preschoolers from low-income families have exhibited lower levels of expressive and receptive language skills (Raviv, Kessenich, Morrison, 2004), lower scores on tests of emergent reading and mathematics (Stipek, Feiler, Daniels, & Milburn, 1995), lower cognitive test scores, and increased levels of behavior problems (Yeung, Linver, & Brooks-Gunn, 2002). Accordingly, many disadvantaged children enter Kindergarten performing substantially behind their peers, initiating a cycle of underachievement that follows them throughout their school careers (Duncan, Yeung, Brooks-Gunn & Smith, 1998; Hodgkinson, 2003; McLloyd, 1998; Stevenson & Newman, 1986).

The income achievement gap is not only evident upon Kindergarten entrance, it also widens as students progress through elementary school (Aikens & Barbarin, 2008; Downey, von Hippel, & Broh, 2004). Low-income children are more often absent from school and kindergarten teachers more often identify them as at risk for academic problems and give them lower marks for behavior (Entwisle & Alexander, 1993). A study of Grade 2 through 4 students found lower income children more likely to perform academically at lower levels and exhibit conduct difficulties than higher-income children (Patterson et al., 1990). Consequently, fewer disadvantaged elementary students excel academically (Wyner, Bridgeland, & DiIulio, 2007; Xiang, Dahlin, Cronin, Theaker, & Durant, 2011).

Poverty continues to have a significant negative association with academic achievement in Grades 6 through 8 (Eamon, 2002) and is evident in middle school students' attitudes and course-taking behaviors. Researchers less often identified low-income eighth-grade students as high achievers on the National Assessment of Educational Progress (Loveless, 2008) and found them less likely to take the Algebra 1 courses that typically serve as gateways to the top high school curriculum tracks (Walston & McCarroll, 2010). Collectively, middle level students from low-income families also express lower expectations for college completion than their higher-income peers (Berkner & Chavez, 1997; Carroll, 1989; Terenzini, Cabrera, & Bernal, 2001). Consequently, disadvantaged students more often enter high school unready for the advanced coursework of a college preparatory curriculum.

Students from low-income families often fall further behind in high school (Center on Education Policy, 2011), disproportionally dropping out of school or inadequately preparing for college (Berkner & Chavez, 1997; IHEP, 2010; King, 1996). Terenzini et al. (2001) found that students from lower-income families were three times less likely to excel in the core subject areas of math, reading, and science, when compared to higher income students. Furthermore, despite increasing opportunities for disadvantaged high school students to take college level Advanced Placement (AP) classes, they have tended to perform poorly in them (Geiser & Santelices, 2004; Hallett & Venegas, 2011). Thus, in 2012-13 approximately one-fourth of AP exam takers were low-income, but three-fourths of low-income exam takers failed to obtain the requisite passing score for potential college credit (ACT, 2014). Similarly, in 2015 the mean SAT scores of students from the lowest income decile were 433 in reading and 455 in math, while the mean scores of students from the highest income decile were 570 in reading, and 587 in math—differences of more than 100 points or a little more than one standard deviation (College Board, 2015).

Postsecondary Achievement Gaps

Over recent decades, rising numbers of students have been attending post-secondary institutions. In 1975, 51% of high school completers entered 2- or 4-year colleges, but in 2012 the proportion had increased to 66% (NCES, 2013c). Much of this improvement was due to a 63% increase in enrollment among low-income students. In fact, several studies have determined that when low-income students demonstrate academic preparedness and complete the college application process they matriculate at comparable rates to students of other income levels (Adelman, 1999; Adelman, 2006; Berkner & Chavez, 1997; Hearn, 1991).

Unfortunately, disadvantaged students less often develop academic preparedness during their K-12 schooling. As a result, students at various income levels have unequal access to postsecondary education. According to Hoxby and Avery (2013),

> many students from low-income families have poor college outcomes: they do not attend college, they drop out before attaining a degree, they earn so few credits each term that they cannot graduate in even 1.5 times the "correct" time to degree, or they attend institutions with such poor resources that even when they graduate, they earn much less than the median college graduate (pg. 5).

Despite rising college enrollments, half of low-income high school graduates do not enroll in postsecondary education (NCES, 2013c; Terenzini et al., 2001). Among those who do enroll, economically disadvantaged postsecondary students have disproportionally needed remedial coursework—particularly in reading (Adelman, 2004). Thus, low-income students consistently remain at greater risk for dropping out of college without obtaining a degree (Adelman, 2004; Alexander et al., 1982; Carroll, 1989; Fitzgerald, Berkner, Horn, Choy, & Hoachlander, 1994; NCES, 2014) and they more often obtain certificates as their highest degrees due to their over-representation in two-year programs (Adelman, Bruce, & Berkovits, 2003; Caroll, 1989; NCES, 2014).

Consequently, despite increasing numbers of low-income students attending college, the gap between low-and high-income students' rates of degree attainment remains wide. In a national longitudinal study, Adelman (2006) quantified the rate of degree completion within eight years for low-income postsecondary students from the high school graduating class of 1992 as 36%, less than half the 80% rate of students from higher-income families. Similarly, the Pell Institute reported that the 2013 bachelor's degree attainment rates by age 24 were 9% for those in the bottom income quartile, compared to 77% for students in the top income quartile—a 68 percentage point gap (Cahalan & Perna, 2015).

Individual Ramifications

Individuals with no more than a high school diploma face a lifetime of insufficient earnings, employment instability, and low socioeconomic status (Baum, Ma, & Payea, 2013; DeNavas-Walt & Proctor, 2014). Although incomes vary by field of study and gender, the Organisation for Economic Co-operation and Development (OECD, 2014) has calculated the average lifetime individual benefits of a U.S. college education to be more than $370,000. Although postsecondary education does not guarantee personal success, it has essentially become the prerequisite for economic prosperity (Carnevale & Rose, 2011). Throughout the world "educational attainment is the measure by which people are being sorted into poverty or relative wealth," (OECD, 2014, pg. 14).

In effect, employers use the four-year college degree as a proxy for the level of an individual's skills (Meyer & Rowan, 2014), placing those without an education at a disadvantage both in finding employment and in bargaining for higher wages. As evidence, one study found that children from low-income families were five times less likely to remain in poverty as adults when they attained a four-year college degree (Baum et al., 2013).

Societal Ramifications

The size of the income achievement gap suggests that a significant proportion of the U.S. population has been under-educated and is accordingly under-contributing to the nation's economy (Hodgkinson, 1999). Throughout the world, healthy economies depend on a sufficient supply of highly skilled, highly educated workers (OECD, 2014, pg. 102). As education levels rise, individual workers become more productive, earn higher wages, and pay more taxes (Baum et al., 2013). This is exemplified by the the OECD (2014) estimate that the U.S. public benefits of an individual college education were over $140,000, which they attributed to increased tax revenues and reduced public expenditures on social welfare.

Over the past 30 years, the U.S. economy's demand for skilled workers has risen at a faster rate than the corresponding supply of highly educated graduates (Autor, 2011; Carnevale & Rose, 2011). By one estimate, 65% of jobs in the year 2020 will require some level of postsecondary education, with a predicted shortfall of five million highly educated workers (Carnevale, Smith, & Strohl, 2013). The current shortage of educated workers and the parallel overabundance of low-skill workers have contributed to an increasing wage premium, with the earnings of college graduates now almost double those of high school graduates. In 2014 the OECD identified the United States as the nation with the highest college wage premium among the countries it studied.

Statement of the Problem

The income achievement gap is pervasive and persistent throughout K-12 schooling and its consequences extend into adulthood. The disproportionate numbers of academically successful, low-income students positioned to obtain the postsecondary degrees that lead to economic prosperity is a central problem in education, negatively affecting not only individuals, but also society as a whole (Olszewski-Kubilius & Thompson, 2010, pg. 59). In light of the importance of this problem, the sustained academic success of low-income students merits particular attention in educational research.

Purposes of the Study

Practitioners and policy-makers who wish to promote the academic achievement of low-income students need empirical data to effectively choose between the wide array of available programs and initiatives. The current study aimed to add to the research base by investigating the relationships between various characteristics of disadvantaged students and the level of sustained K – 12 academic success that allowed them to enter postsecondary education prepared to complete a degree. The focus of the study sought to go beyond theoretical explorations of income, risk, and achievement to identify behaviors and school conditions that may be helpful to educators and policy-makers designing initiatives that foster the long-term success of low-income students.

Research Questions

Question 1. What level of cumulative risk exposure is associated with postsecondary degree completion?

Question 2. What level of income is associated with elevated proximal risk exposure?

Question 3. What level of academic achievement is associated with academically successful postsecondary degree completion?

Question 4. Which individual, family, and school characteristics are related to low-income students' academic success?

Definition of Terms

Academically successful—For the purposes of the study, academic success is educational performance at a level associated with greater odds of postsecondary degree completion.

Adaptive processes—interactions between individuals and their environments that that promote successful functioning, typically falling into the categories of individual attributes, family supports, and external supports (Masten, 2001).

Cumulative risk count— a measure of individual risk levels by tallying exposure to specified adversities and negative life events (Evans & Kim, 2010).

Distal risk—membership in a group with a statistically high probability of lower functioning in a targeted developmental domain (Catterall, 1998; Luthar, 1993).

Extracurricular activity—For the purposes of the study, extracurricular activities include students' unpaid participation in organized activities outside the regular school day, including sports, clubs, community groups, and community service.

Non-resilience— negative developmental outcomes in a targeted domain exhibited by an individual who has been exposed to significant adverse conditions or experiences.

Positive adaptation—interactions between an individual's personal characteristics and the conditions in his or her environment that result in successful functioning.

Proximal risk—direct exposure to adverse conditions that have been associated with lower functioning in a targeted developmental domain (Catterall, 1998; Luthar, 1993).

Resilience—an individual's successful adaptation in a targeted developmental domain despite exposure to significant adversity (Luthar, Chicchetti, & Becker, 2000; Masten, 2001).

Resiliency—a discrete personality trait related to ready recovery from personal setbacks. For the purposes of the study, an unhelpful term that fails to account for the importance of an individual's environmental supports (Luthar et al., 2000).

Risk factor—adverse conditions with "proven or presumed effects that can directly increase the likelihood of a maladaptive outcome" (Rolf & Johnson, 1990, p. 387)

Significant adversity—severe negative events or conditions that present a serious threat to an individual's adaptation or development (Luthar et al., 2000)

CHAPTER 2

Literature Review

The current study's purpose was to develop a better understanding of how to promote the academic success of low-income K-12 students and position them for eventual postsecondary degree completion. With this in mind, the following analysis evaluates the literature as it relates to these basic questions: (a) Which risk factors have been associated with low-income status? (b) How have researchers distinguished academically successful, low-income students? (c) Which characteristics and conditions have been related to low-income students' academic success?

Various researchers have explored and documented how low-income status has been detrimental to children's wellness in early childhood (Hodgkinson, 2003), socioemotional and cognitive functioning (McLoyd, 1998), academic engagement and self-efficacy (Lucio, Hunt, & Bornolova, 2012), and overall school achievement (Burney & Beilke, 2008). Rather than focusing on how low-income students often underperform, the current study sought to better understand the mechanisms that "explain why so many poor children perform well in school despite restricted material resources" (Davis-Kean, 2005, p. 302). Thus, this literature review concentrates on researchers who have studied the small, but substantial, group of academically successful low-income students. Much of the scholarly literature related to mechanisms that explain successful developmental outcomes despite exposure to developmental threats falls into the category of *resilience*.

The construct of resilience grew out of Norman Garmezy's (1971) attempts to explain why some people at high risk for pathology thrive rather than succumb, and Michael Rutter's (1985) work identifying protective attributes and behaviors that enhance resistance to psychiatric disorders. In the Kauai longitudinal study that tracked children from the perinatal period to adulthood, Emmy Werner and her colleagues (1994; Werner, Bierman, & French, 1971; Werner & Smith, 1977) extended the field of resilience to socioeconomic disadvantage and its associated risks. Later, Ann Masten and her colleagues (1988) further developed the construct of resilience in the school domain, examining student competence in the areas of social engagement, classroom behavior, and academic achievement. Despite their varying foci, these early researchers were alike in their search for the qualities and conditions that differentiated individuals with positive outcomes despite their exposure to adverse risk conditions.

In the ensuing years, widely varying research in the field of resilience has resulted in ambiguous terminology and theoretical underpinnings, as highlighted by Suniya Luthar in numerous publications (Luthar, 1993; Luthar et al., 2000; Luthar, Sawyer, & Brown, 2006). In an attempt to clarify the construct, Luthar et al. (2000) defined resilience as "a dynamic process encompassing positive adaptation within the context of significant adversity" (p. 1). This definition points to three areas that required clarification and identified relevant literature for the current study: (a) the presence of significant adversity or risk factors, (b) the domain of positive adaptation, and (c) the dynamic process of adaptation.

Although most resilience researchers define resilient individuals as those who have been exposed to significant adversity or risk (Luthar et al., 2000), the term *resilience* has been co-opted by some researchers to describe success in the face of common academic challenges (Martin, 2002; Martin & Marsh, 2006; Schoon & Duckworth, 2010; Yeager & Dweck, 2012) or setbacks (Cappella & Weinstein, 2001;

Catterall, 1998), regardless of adverse risk exposure. Martin (2013; Martin, Colmar, Davey, & Marsh, 2010) later coined the term *academic buoyancy* to describe what he considered to be an "everyday" form of resilience, but the term has not yet reached common usage in this low-risk context. Because the current study was concerned with students from low-income backgrounds, this literature review primarily focuses on studies concerned with low-income status as an adverse risk exposure and excludes resilience studies involving children who have not been exposed to adverse risks.

Resilience researchers have explored positive adaptation using myriad outcomes including social competence (Garmezy, Masten, & Tellegen, 1984), emotional functioning (Rutter, 1987), and academic performance (Borman & Rachuba, 2001; Borman & Overman, 2004; Finn & Rock, 1997). Due to the current study's focus on academic success, this literature review includes studies that addressed successful academic performance and excludes literature that explored other forms of positive adaptation. However, this analysis incorporates research that used multiple outcomes when at least one of them measured academic success (e.g., Bondy, Ross, Gallingane, & Hambacher, 2007).

Resilience researchers typically explore processes of adaptation that facilitate successful development (Luthar et al., 2000; 2006; Masten, Best, & Garmezy, 1990). The term *resilience* describes successful adaptive interactions between individuals and their environments, rather than a singular personal characteristic that individuals either possess or lack. Within the field of resilience there is considerable confusion surrounding the vocabulary that distinguishes variables promoting positive outcomes for most individuals from those that are particularly beneficial for individuals exposed to adverse risks factors

(Luthar 1993; Luthar et al., 2000; 2006). In particular, Luthar points out that the word *protective* has been used to describe both types of adaptive processes. While resilience researchers may be motivated to isolate and identify variables that are more beneficial for some individuals than others, in the context of the current study there was no practical reason to make this distinction—any characteristic or condition that promoted the academic success of low-income students was of interest, regardless of whether or not it also provided equal benefit for students at other income levels. Consequently, this literature review focuses on identifying characteristics and conditions that lead to academic success for low-income students without undue focus on adaptive process terminology or the effects of those processes on higher income students.

Risk Factors

Dawber and Kannel (1966) first used the term *risk factor* in relation to behaviors and conditions that negatively affect cardiac health. In the context of resilience, risk factors have been generally defined as “proven or presumed effects that can directly increase the likelihood of a maladaptive outcome” (Rolf & Johnson, 1990, p. 387). Examples of risk factors related to poor child development included death of a parent (Greeff & Berquin, 2004), maltreatment (Schelble, Franks, & Miller, 2010), maternal drug abuse (Luthar & Sexton, 2007), parental divorce (Kelly & Emory, 2003), gang violence (Li, Stanton, Pack, Harris, Cottrell, & Burns, 2002), community violence (Overstreet & Braun, 1999), learning disabilities (Morrison & Cosden, 1997), mental illness (Garmezy, 1991), immigrant status (Chrispin, 1999; Perez, Espinoza, Ramos, Coronado, & Cortes, 2009), and ethnic or racial minority status (Gonzalez and Padilla, 1997; Hawkins & Mulkey, 2005). Of greatest importance to the current study, researchers have repeatedly found low-income status be the most important variable associated with poor academic outcomes in children (Abbott & Joireman, 2001; Alexander et al., 1982; Entwisle & Alexander, 1993; McLoyd, 1998; Patterson et al., 1990; Peng & Wright, 1994). The resilience literature related to risk factors raised important considerations for the current study in the areas of risk proximity (Luthar, 1993) and cumulative risk exposure (Evans & English, 2002).

Risk Proximity

Resilience experts differentiate between *distal* risks, which are statistically high probabilities of failure associated with membership in certain groups, and *proximal* risks, which involve direct exposure to adverse conditions (Catterall, 1998; Luthar, 1993). Distal risks, such as low-income status, generally affect children through their corresponding proximal risks (Felner et al., 1995; Sameroff, Seifer, Baldwin, & Baldwin, 1993). For example, families with the distal risk of poverty may have limited money to buy food, subjecting them to the proximal risk of food insecurity, leading to malnutrition that may impair children's neurodevelopment (Cook & Frank, 2008). Thus, the distal risk of low-income status indirectly causes impaired neurodevelopment, through the direct, proximal risk of food insecurity.

Proximal risks associated with poverty. In essence, poverty serves as a proxy for a set of proximal risks that may be more difficult for researchers to identify or measure. Rouse and Fantuzzo (2009) reinforced the importance of proximal risks in their large-scale study of 10,349 Grade 2 students, which concluded that the proximal risks that often co-occur with poverty were often more predictive of achievement test scores than poverty itself. Although Rouse and Fantuzzo (2009) studied the particular income-related proximal risks of birth risk, homeless experience, and maltreatment, other proximal risks have also been associated with poverty and adverse academic outcomes. The list of income-related proximal risks includes exposure to lead (McLoyd, 1998; Rothstein, 2008), poor health (Hanson, Austin, & Lee-Bayha, 2003; Hodgkinson, 2007; Rothstein, 2008, Rutter, 1987), exposure to stressful life events (Gutman, Sameroff, & Eccles, 2002; Sameroff et al., 1993), family conflict and upheaval (Evans & English, 2002; Greenberg et al., 1999), inadequate community support (Greenberg et al., 1999; Leventhal & Brooks-Gunn, 2000), housing insecurity (Addy & Wight, 2012; Burney & Beilke, 2008; Leventhal & Brooks-Gunn, 2000; Rouse & Fantuzzo, 2009), single parent status (Addy & Wight, 2005; DeNavas-Walt & Proctor, 2014; Evans, 2003), low parental warmth or support (Davis-Kean, 2005; Mullis, Rathage, & Mullis, 2003; Robinson, Lanzi, Weinberg, Ramey, & Ramey, 2002), parental psychological distress or depression, (Burchinal, Roberts, Zeisel, & Rowley, 2008; Gutman et al., 2002; Sameroff et al., 1993), and low parental cognitive stimulation (McLoyd, 1998; Rothstein, 2008).

Identifying children placed at proximal risk. It is important to differentiate between distal and proximal risks because some successful low-income children identified as *resilient* due to presumed risk exposure may have actually faced few directly adverse proximal conditions (Luthar, 1993). For this reason, the generalizability of findings from research studies involving low-income status is particularly dependent upon selection criteria that accurately identify individuals most likely to have been placed at proximal risk. In particular, overly broad low-income identification criteria may include a number of individuals with lower risk exposures. Exemplifying this problem, a foundation-sponsored comparison study of high achieving students from lower and higher income families from the nationally representative 1998 ECLS data set (Wyner et al., 2007) reported that between Grades 1 and 5, lower income high achievers dropped from 6.9% to 6.0% of the overall group. The findings may have underreported the negative relationship between low-income status and sustained high achievement because the authors' methodology split the sample into only two groups for the main income comparisons, rather than dividing the sample into quartiles or quintiles as other researchers have done (e.g., Adelman, 1999; Aikens & Barbarin, 2008). Thus, the two-group comparison included students from families with incomes near the median—and potentially lower risk exposures—in the lower income category.

National School Lunch Program eligibility and proximal risk. Another problematic, but common, low-income selection criteria used in education research is National School Lunch Program eligibility (Harwell & LeBeau, 2010). Researchers who use this method seldom differentiate between the poorer students eligible for free meals and those with higher incomes that are only eligible for reduced meals (e.g., Abbott & Joireman, 2001; ACT, 2014; Bentzel, 2012, Caldas & Bankston, 1999)—currently families earning up to 185% of the Federal poverty guidelines (Department of Agriculture, 2015). The 2015-2016 reduced meal benchmarks of $44,863 for a family of four and $75,647 for a family of eight suggest qualitatively different lifestyles, and thus differential proximal risk exposures, than those experienced by families living on substantially lower incomes. Furthermore, as many as 20% of the students identified as low-income by school lunch participation may have been misclassified due to errors in the certification process and participation declines at higher grade levels (Harwell & LeBeau, 2010).

Illustrating the problems associated with using National School Lunch Program eligibility as an identifier, Xiang et al. (2011) conducted a study using a sample of 14,000 students from 29 states in Grades 3 through 9 from 2004 to 2010. Xiang et al. (2011) used the top decile of scorers on Measures of Academic Progress assessments in mathematics and reading and identified low-income students by their attendance at a high poverty school—defined as more than 50% of students qualifying for the National School Lunch Program. Xiang et al. (2011) found that the proportion of low-income high achievers in math declined from 19% to 16%, between Grades 3 and 8 and from 18% to 15% between Grades 6 and 9. The findings are undermined by methodology that potentially misidentified higher income students as low-income students. The authors not only used the broad criteria of National School Lunch Program participation, they also compounded the problem with "ecological fallacy" (Sirin, 2005) by identifying all students in a school as low-income if at least half of the students in the school qualified for free or reduced lunch. Misidentification was particularly likely in this study because up to 49% of the students in the school may have exceeded the lunch program income benchmarks and higher income students are statistically more likely to be high achievers.

Federal poverty measures and proximal risk. Even if researchers were to distinguish between students eligible for free and reduced lunch, federal poverty measures were not designed to indicate a specific level of income where risk exposures and adverse outcomes for children become more or less likely (Fisher, 2001). The United States has two official measures of poverty: (a) the poverty threshold issued by the U.S. Census Bureau for statistical purposes and (b) the poverty guidelines issued by the Department of Health and Human Services to determine eligibility for government assistance programs (Fisher, 1997). The poverty guidelines are merely a simplified version of the poverty threshold, with minimal cost adjustments for residents of Alaska and Hawaii. The official poverty thresholds were originally developed by Molly Orshansky in the 1960s and have not taken into account geographic differences in the cost of living or changes in standards of living over the past 50 years (DeNavas-Walt & Proctor, 2014). Although the poverty thresholds are adjusted for inflation each year using the Consumer Price Index, they are still based on triple the cost of purchasing what was determined to be a minimal nutritionally adequate amount of food in 1955 (U.S. Department of Health & Human Services, n.d.). Consequently, federal poverty guidelines offer little utility for researchers seeking to identify individuals exposed to elevated levels of proximal risk because the benchmarks bear no relationship to the actual costs of goods and services people need to maintain health and employment, such as medical care, housing, transportation, and child care (Citro & Michaels, 1995; Fisher, 1997).

Cumulative Risk Exposure

According to Evans and English (2002), the accumulation of risk factors may be a "unique, key aspect of poverty" (p. 1244). At lower income levels individuals are more likely to have been exposed to multiple proximal risks (Evans & English, 2002; Evans & Kim, 2010). In turn, cumulative risk exposure has been negatively correlated with academic achievement (Robinson et al., 2002; Rouse & Fantuzzo, 2009). As evidence, a study of 837 African American students in Grade 7 found a significant negative relationship between the number of risk factors and math achievement in students with low levels of peer support (Gutman et al., 2002). Additionally, a study of school-related risks in a nationally representative sample of 14,736 high school students found that the odds of students dropping below a 2.0 GPA increased 47% with each added risk (Lucio et al., 2012).

Researchers have also posited that the accumulated number of risks is more important than the pattern of risk (Evans & Kim, 2010; Rutter, 1987). Sameroff et al. (1993) conducted a longitudinal study of 152 families, examining the children at 4 and 13 years of age to determine the relationships between 10 specified risk factors and IQ. The 10 risk factors were combined into an aggregated index in several regression analyses. Not only were the risk exposures fairly stable over the 9-year period, the cumulative risk index was robust in predicting IQ over time, with mean IQs dropping from around 115 to 90 from 0 to 4 risk factors, but remaining relatively flat at a mean IQ of 90 from 4 to 9 risks. When the authors used cluster analysis to detect meaningful patterns of risk across families, IQ scores did not vary significantly between the identified clusters after adjusting for number of risks. The results suggest that although certain risk factors tend to co-occur in low-income families, varying patterns of risks do not have differential effects on children's IQs. Notably, Sameroff et al. (1993) did not differentiate between distal risks (e.g., parent occupation, mother's education) and proximal risks (e.g., family social support, major stressful life events, mother's behavior), including both together in their risk index.

In light of the importance of accumulated risk, resilience researchers commonly use cumulative risk counts of variables with dichotomous outcomes to represent multiple risk exposures (Evans & Kim, 2010). According to Evans and Kim (2010), cumulative risk counts are efficacious because they require smaller sample sizes than multiple singular risk variables. Particularly large sample sizes would be required to examine the interaction effects between risk factors while maintaining statistical power. Moreover, cumulative risk models are more appropriate when studying low-income students because many proximal risks covary, which precludes interactive models that are sensitive to multicollinearity between independent variables.

Academically Successful Students

To study low-income, academically successful students, researchers must first identify them. Unfortunately, scholarly literature lacks a standardized definition of academic success. Resilience researchers, in particular, often consider positive adaptation to be performance relative to the level of exposure to trauma or risk (Luthar, 2000). Therefore, some researchers defined academic success as the absence of failure, and thus used indicators related to average achievement. The "absence of failure" approach was exemplified by Fin and Rock's (1997) academic success benchmarks that included merely passing grades, standardized test scores above the 40th percentile, and high school graduation. Similarly, Gordon (1996) and Lucio et al. (2012) used the benchmarks of 2.75 and 2.0 grade point averages (GPA), respectively, which are both in the C-average range. These benchmarks hardly differentiated the academic success that leads to the postsecondary degree completion that lifts people out of poverty (Baum et al., 2013). Even after refocusing my analysis on indicators that specifically distinguished high achievement, I found that the benchmarks still varied widely in both accepted performance levels and indicator types. My analysis yielded five indicator categories: (a) standardized achievement test scores, (b) GPA, (c) advanced coursework, (d) postsecondary matriculation, and (e) gifted designation.

Standardized Achievement Test Scores

Across grade levels, most researchers used standardized test scores to identify high achievers. The popularity of standardized tests is most likely due to their quantified reliability and validity, the availability of normative or criterion references, and numerical scoring that is amenable to myriad statistical procedures. Although researchers have found standardized test scores to be positively associated with educational outcomes, such as successful degree completion (Geiser & Santelices, 2004; Adelman, 1999), they have also found them less accurate than GPA (Geiser & Santelices, 2004) or advanced course taking (Adelman, 1999).

I found it relatively uncommon for studies to use criterion rankings, such as the designation of *Advanced* on state tests (Center on Education Policy, 2011). Instead most studies used a particular percentile rank on a nationally normed test. The designated national percentile benchmarks generally ranged from the top 10% (Loveless, 2008) to the top 25% (Wyner et al., 2007), whereas, the occasional study used a local norm, such as the top 3% of scorers from a cohort of former Head Start students (Robinson et al., 2002) or the top 10% in a high poverty school (Xiang, et al., 2011). The type of assessments varied widely, with differing studies using the Early Childhood Longitudinal Program academic assessments (Wyner et al., 2007), the SAT and ACT (Hoxby & Avery, 2013), the Northwest Evaluation Association's Measures of Academic Progress (Xiang et al., 2011), the California Test of Basic Skills (Borman & Overman, 2004; Borman and Rachuba, 2001), the National Assessment of Educational Progress (NAEP) (Loveless, 2008), the Woodcock-Johnson Tests of Achievement, and the Peabody Picture

Vocabulary Tests (Robinson et al., 2002). These achievement tests differ in their targeted populations, frequency of testing, and content, due to their varying purposes.

GPA

The studies that used GPA to designate high achievement involved high school or middle school students, most likely due to infrequent use of GPA and class ranking at the elementary level. In addition to inconsistent use across school levels, the efficacy of GPA is also limited by variability in grading policies across schools, rendering it most useful for indicating relative achievement of students within a school (Adelman, 1999). The GPAs that distinguished high achievers were 3.0 or B average (Antrop-Gonzalez, Velez, & Garrett, 2005), 3.5 or B+ average (Lawrence, 2014), and 3.7 or A- average (Hoxby & Avery, 2013). Although the first two listed studies relied solely on GPA as reported by school officials, Hoxby and Avery (2013) used students' self-reported GPA in combination with SAT scores for identifying successful students.

Advanced Coursework and Postsecondary Matriculation

Rather than focusing on quantitative benchmarks, a few studies distinguished high-achieving middle school or high school students by their academic behaviors, such as advanced course taking. The studies that used advanced course taking as identifying criteria used enrollment in advanced math (Schreiber, 2002); honors courses and AP classes (Perez et al., 2009; Tyson et al., 2005); or a passing score of 3, 4, or 5 on an AP test (Burney, 2010). Using a different behavioral approach, one study differentiated high-achieving students by their acceptance into a selective or highly selective college or university (Hallett & Venegas, 2011). Unfortunately, the behavioral approach to identifying successful students is problematic due to unequal access, particularly for minority, low-income, and rural students who are more likely to attend schools offering few or no advanced courses (Adelman, 1999; Geiser & Santelices, 2004) and who are less likely to apply to selective colleges (Hoxby & Avery, 2013).

Gifted Identification

A considerable proportion of the research on low-income, high-achieving students has emerged from the field of gifted education. Because the focus of gifted educators is on developing individuals of eminence (Burney & Beilke, 2008; Dai & Chen, 2013; Subotnik, Olszewski-Kubilius, & Worrell, 2011), gifted identification typically depends upon strict selection criteria related to intelligence aptitude. Gifted benchmarks included an IQ of 130 or above (Gottfried, Gottfried, & Guerin, 2006) or intelligence test performance at or above the 98th (Pendarvis & Wood, 2009) or 99th percentiles (Freeman, 2006; Kitano & Lewis, 2007). These stringent requirements render gifted research the study of statistical outliers and, consequently, of limited generalizability to a wider population (Subotnik et al., 2011). For these reasons the current analysis excludes most literature related to gifted education.

Characteristics Related to Academic Success

Although risk is an important part of resilience research, recent theorizing about academic resilience has moved away from a focus on risk to a more proactive approach focused on the processes that enable successful adaptation in the face of adversity (Luthar, 2006). Although some resilience researchers use the terms *protective, promotive,* and *compensatory* to describe processes associated with success for individuals with differential risk exposure, there is substantial disagreement on the definitions and proper usage of these terms (Luthar, 1993; 2000; 2006). Due to this lack of consensus, the current analysis groups protective, promotive, and compensatory adaptive processes together into the general category of *adaptive characteristics* that promote low-income students' success, in alignment with the practices of several other resilience researchers (e.g., Borman & Overman, 2004; Finn & Rock, 1997; Hébert & Reis, 1999). These characteristics fall into the categories of individual attributes, family supports, and external supports (Masten & Coatsworth, 1998).

Individual Attributes

Researchers have identified several attributes related to the ability of low-income students to maintain academic success. These attributes include self-esteem, self-efficacy, and internal locus of control, (Borman & Overman, 2004; Finn & Rock, 1997; Garmezy, 1991), emotional regulation (Schelble et al., 2010), goal setting (Garmezy, 1991; Reis, Colbert, & Hébert, 2005), cognitive skills (Garmezy, 1991; Perez et al., 2009), and a sociable temperament that engenders support from others (Garmezy, 1991).

Some experts caution that individual attributes commonly related to resilience may actually be "consequences of success rather than causes of it" (Masten & Coatsworth, 1998, p. 213). For example, self-efficacy may be considered both the result of and the precursor to competence. To determine the directionality of characteristics related to academic success, a group of researchers studied 1,866 Australian high school students to develop a model that best predicted standardized achievement test scores (Green et al., 2012). The most effective model was one where self-concept and academic motivation predicted attitudes toward school, which in turn predicted positive school behaviors, which were finally associated with test performance. These findings, while not definitive, do provide support for the theory that self-efficacy may be considered a precursor to success.

Any focus on individual attributes must take care to differentiate between *resiliency* as a discrete personality trait and *resilience* as a process of adaptation (Masten, 2001). Solely focusing on individual characteristics can lead to the misinformed judgment that resilience is something individuals either do or do not have, thus removing the incentive to offer external supports. In fact, resilience experts recognize that "resilience may often derive from factors external to the child" (Luthar, 2000, p. 2) both within and external to the family unit.

Family Supports

While researchers have identified several parent and family characteristics as risk factors (e.g., Davis-Kean, 2005; Gutman et al., 2002; McLoyd, 1998), families can also act to buffer the effects of adverse environments on their children (Garmezy, 1991). The supportive parent characteristics and behaviors associated with academic success in low-income children include expressing a value for education (Hébert & Reis, 1999; Perez et al., 2009); holding high expectations for achievement (Davis-Kean, 2005; Finn & Rock, 1997; Stage & Hossler, 1989); having a warm, supportive, and positive interaction style (Davis-Kean, 2005; Robinson et al., 2002); showing respect for children's individuality (Garmezy, 1991); providing a religious home environment (Reis et al., 2005); and high cognitive stimulation, such as family reading behaviors (Davis-Kean, 2005; Hsin, 2009). It is particularly notable that certain family characteristics, such as parental warmth (Davis-Kean, 2005; Robinson et al., 2002) and parental cognitive stimulation (Davis-

Kean, 2005; McLoyd, 1998) are considered both adaptive characteristics and risk factors, depending upon whether they are present at the higher or lower ends of the continuum.

Some results suggest that the effects of parental characteristics and behaviors may differ across contexts. Hsin's (2009) study of 1,008 preschool-aged children determined that time spent with parents only enhanced children's cognitive development when the parents were at the higher end of the language ability continuum and were more able to provide cognitive stimulation and verbal engagement. Additionally, a study of 45 African American middle school students exposed to community violence found that students from families with high achievement expectations and a strong emphasis on religion had the highest academic functioning at low levels of exposure to violence. However, at high levels of exposure they were most at risk of poor functioning, suggesting that some protective attributes and behaviors may not be consistent across risks (Overstreet & Braun, 1999).

External Supports

Children who have been exposed to adverse risk factors often benefit from supportive relationships beyond their families of origin to achieve sustained academic success (Condly, 2006). Although local community norms and opportunities for engagement can support children's success, school is a major source of external support for children (Wang, Haertel, & Walberg, 1997). My analysis of the literature uncovered three school-related characteristics that foster academic success in low income students, (1) a safe and supportive culture, (2) extracurricular participation, and (3) supportive peers.

Safe and supportive school culture. Several studies have investigated the relationship between school culture and academic achievement. To determine school level features related to academically resilient students, Borman conducted a longitudinal study of 3,981 diverse low-income students from Grades 3 through Grade 6 (Borman & Overman, 2004; Borman & Rachuba, 2001). The study used data from Prospects: The Congressionally Mandated Study of Educational Growth and Opportunity to compare four school models and determine their associations with math achievement test scores as well as interaction effects related to race and ethnicity. The four models were (a) Effective Schools, (b) Peer-Group Composition, (c) School Resources, and (d) Supportive Communities. The study included only students who were in the lower third of the SES distribution of composite scores that combined income, occupation, and parent education levels. The authors divided the low-income children into two groups, labeling them *resilient* when their math performance was better than predicted by an equation based on prior achievement levels and labeling the remaining students *non-resilient*. Using multivariate analysis of variance (MANOVA) tests the authors determined that the Effective Schools, Peer-Group Composition, and School Resources models did not significantly distinguish resilient from non-resilient students. However, the Supportive Communities model was significantly associated with resilience, particularly the variables related to a safe and orderly environment and positive teacher and student relationships. The authors concluded that a school's concentration of underrepresented minority students, class sizes, levels of teacher experience, and availability of instructional supplies were not associated with math achievement among low-income African American, Hispanic, and White students. However, Borman et al.'s

(2004) findings should be interpreted with caution because their methodology used low-level criteria for academic success—the resilient groups' Grade 6 median math scores were at the 59th percentile.

Despite the aforementioned limitation, Borman et al.'s (2004) findings are congruent with those of other studies. The lack of significant findings related to school resources aligns with the results of the landmark Coleman Report (1966), which assessed educational equity in terms of curriculum, school facilities, teacher characteristics, and academic achievement, finding that—despite wide variation in school conditions—the differences accounted for only a small fraction of student achievement. Additionally, a meta-analysis by Wang et al. (1997) determined that providing a safe and orderly environment through effective classroom management was the educational practice with the greatest influence on learning.

Additional evidence supports the importance of teacher-student relationships in promoting academic success (Plunkett, Henry, Houltberg, Sands, & Abarca-Mortensen, 2008; Wang et al., 1997). Sharkey, You, and Schnoebelen's (2008) examination of survey data from 10,000 diverse Grade 7, 9 and 11 California students determined that engagement in school increases when students identify an adult at school who cares about them, supports them, and encourages them to do their best. Similarly, the authors of a study of academic resilience in Latino high schools students determined that a sense of belonging in school and ample teacher feedback were the only significant predictors of GPA (Gonzalez & Padilla, 1997). Furthermore, qualitative evidence from videotapes of three effective novice elementary teachers in high poverty schools showed that student resilience was bolstered by teachers who focused on building relationships, establishing clear expectations, and communicating supportive messages (Bondy et al., 2007).

Extracurricular participation. The relationship between participation in extracurricular clubs or sports and academic success has been well documented (e.g., Broh, 2002; Feldman & Matjask, 2007; Lipscomb, 2006). Two studies using time journal data found positive effects on academic achievement for students of all income levels aged 5 to 18 who were involved in extracurricular activities (Hofferth & Sandberg, 2001; Mahoney, Harris, & Eccles, 2006). Another study found positive relationships between participation in athletics and educational aspirations and academic investment behaviors for African American middle school students from a National Education Longitudinal Survey of 1988 (NELS:88) sample that was 44% low-income (Hawkins & Mulkey, 2005). Additionally, a study of 110 undocumented immigrant high school and college students used hierarchical regression and cluster analysis to find that the most significant predictors of academic success—as measured by high school GPA and rigorous course work—were parental valuing of school, extracurricular participation, and volunteerism (Perez et al., 2009).

By contrast, in a study with a completely low-income sample, Finn and Rock (1997) determined that extracurricular and sports participation were not significant differentiators between resilient and non-resilient students. Similar to Hawkins and Mulkey (2005), Finn and Rock (1997) used a sample from NELS:88, but they included both African American and Hispanic students from Grade 8 through Grade 12 and chose their sample from the lower half of the SES distribution using a composite based on parent education, parent occupation and household income. Finn and Rock also used a relatively low standard for academic success that included passing grades, standardized test scores above the 40th percentile and on-time graduation. As a result, the authors found no significant differences between resilient and non-resilient students related to extracurricular participation, but they did find positive effects for self-esteem and locus of control. They also found that the mean family income of resilient students ($17,500) was significantly higher than that of non-resilient students ($10,000), which may point to differential proximal risk exposures between the two groups.

Supportive peers. Although peers can be supportive of academic achievement, they may also motivate underachievement. Before James Coleman (1966) issued his landmark report on educational equality, he published a study (1961) documenting how high school adolescents undermined their high achieving peers' scholastic achievements through ridicule and exclusion. Since that time, multiple researchers have studied the relationship between student underachievement and peer relations (e.g., Boehnke, 2007; Eisenberg, Neumark-Sztainer, & Perry, 2003), particularly in relation to gifted (e.g., Manor-Bullock, Look, & Dixon, 1995; Swiatek, 1995) and African American students (e.g., Fordham & Ogbu, 1986; Fryer & Torelli, 2010; Horvat & Lewis, 2003; Ogbu, 2004; Tyson et al., 2005).

A qualitative exploratory study documented the positive effects of a supportive peer group, as well as other characteristics, on mainly low-income high achievers (Hébert & Reis, 1999; Reis et al., 2005). During this extensive project, researchers observed 17 underachieving and 18 high-achieving, high-ability high school students from diverse racial and ethnic backgrounds in the urban Northeast over a period of three years, for a total of 180 days at various times in both school and community activities. The researchers defined *high ability* as student achievement at or above the 90th percentile on a standardized intelligence or achievement test using local norms. They defined *high achievement* as superior performance in one or more academic area in elementary or secondary school on three of four measures that included (a) high grades, (b) gifted program participation, (c) teacher or counselor nomination, and (d) academic awards. They defined *underachievement* as previous high achievement followed by a current GPA of 2.0 or lower, lack of college-bound coursework, and habitual truancy or dropping out of high school. In addition to their extensive observations, the researchers interviewed the students' teachers, administrators, coaches, guidance counselors, parents, and community members. They found that high-achieving students (a) relied on support from other high-achieving students; (b) identified a positive relationship with an influential teacher or guidance counselor; (c) actively participated in numerous clubs, sports, and summer programs; and (d) relished the challenges of high level honors and AP classes (Hébert & Reis, 1999). Conversely, underachieving, high-ability students more often (a) had difficulty establishing peer networks, (b) experienced negative interactions with teachers, (c) had excessive unstructured time, and (d) found their classes boring and unchallenging (Reis et al., 2005). Furthermore, although both types of students experienced temporary periods of lower achievement, the underachieving group demonstrated lower self-efficacy and was less likely to persevere after setbacks, making it difficult for them to recover their former levels of high achievement.

Summary

The majority of the literature on low-income, academically successful students employed non-experimental designs, quantitative methods, and large national data sets, although I also found an occasional in-depth, longitudinal study. Together the findings suggested that low-income students achieve academic success in disproportionately lower numbers to their higher income peers. Low-income individuals who did achieve sustained academic success tended to exhibit the qualities of self-esteem, self-efficacy, goal setting, emotional regulation, and sociability. Families of academically successful students were more likely to value education, hold high expectations for achievement, exhibit warmth and support, and promote cognitive stimulation. Although school resources and demographics were not found to be important, sustained success for low-income students was related to safe and orderly school environments, caring and supportive teacher relationships, and opportunities for high-achievers to find support from like-minded peers. Conversely, the contradictory findings related to extracurricular participation and academic success, particularly for low-income students, suggested an area for further investigation.

The literature identified low-income status to be a distal, or statistical risk, that serves as a proxy for direct exposure to adverse conditions. Because evidence suggested that unfavorable outcomes for children increase as their cumulative proximal risk exposures increase, findings from the literature were undermined by inconsistencies in identifying low-income students. Specifically, the methodology for identifying low-income students sometimes used broad income categories that potentially included students with lower exposures to proximal risk in the low-income group. In particular, Federal School Lunch Program eligibility posed threats to the validity of some studies.

The ability to generalize findings also suffered from definitions of academic success that were so widely varying they covered very different types of learners—from nearly gifted to fairly average. The majority of the academic selection criteria used a round number cutoff, such as the 10th or 25th percentile, on a standardized test without considering the future utility of achievement at the given level. Of greatest concern were the studies of academic resilience that defined academic success as “good enough to graduate,” although students without sufficient levels of academic resources to complete some type of postsecondary education are hardly positioned for success beyond high school (Baum et al., 2013; DeNavas-Walt & Proctor, 2014).

Considering these inconsistencies in differentiating academic success and low-income status, I found it difficult to discern whether the aforementioned characteristics related to academic success were generalizable to the individuals of interest to the current study. Without accurate information, educators and policy-makers are less able to make informed decisions that will help the most vulnerable students enter postsecondary education prepared to complete a degree and demonstrate economic success in adulthood. Given these limitations, the current study investigated the following questions.

Question 1. What level of cumulative risk exposure is associated with postsecondary degree completion?

Question 2. What level of income is associated with elevated proximal risk exposure?

Question 3. What level of academic achievement is associated with academically successful postsecondary degree completion?

Question 4. Which individual, family, and school characteristics are related to low-income students’ academic success?

CHAPTER 3

Methods

The current study's purpose was to identify conditions that support academic success among low-income students and develop an understanding of how to enable a greater proportion of them to enter postsecondary education prepared to complete a degree. Therefore, the study sought to identify both the low-income students most likely to have been placed at elevated proximal risk and the academically successful students most likely to obtain postsecondary degrees. Four questions guided this research.

Question 1. What level of cumulative risk exposure is associated with postsecondary degree completion?

Question 2. What level of income is associated with elevated proximal risk exposure?

Question 3. What level of academic achievement is associated with academically successful postsecondary degree completion?

Question 4. Which individual, family, and school characteristics are related to low-income students' academic success?

Data Set

The main source of data was the Panel Study of Income Dynamics (PSID) public-use data set produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor (2015). The PSID is an active longitudinal study initiated in 1968 with a nationally representative sample of 5,000 U.S. families. Until 1997, PSID researchers annually interviewed each original family and its offshoots (e.g., grown children who established their own households), but after that time the expense associated with contacting the growing sample prompted the study to switch to biannual interviews (McGonagle, Schoeni, Sastry, & Freedman, 2012). The PSID has attempted to follow members from the original families for almost 50 years, resulting in a data set that includes details on over 48,000 variables related to economic conditions, personal wellness, and health. The PSID response rates have ranged over the years from 77% to 99% (Institute for Social Research, 2013). Although lower income families have had higher attrition from the PSID, researchers have concluded that cumulative effects have not biased the study's national representation of health and economic factors (McGonagle et al., 2012). Because the PSID is a longitudinal study of *income* dynamics, it is a particularly strong and reliable source for data regarding risks and outcomes associated with poverty.

In 1997 the PSID initiated the Child Development Supplement (CDS) to provide longitudinal data on 3,563 children, studying a maximum of two randomly chosen children from 2,394 PSID families at five-year intervals—1997, 2002, and 2007 (Hofferth, Davis-Kean, Davis, & Finkelstein, 1997). The CDS served an ideal source of information for the current study, due to its nationally representative database of young children with extensive information in the areas of psychosocial wellness, health, and academic achievement from time diaries, interviews, achievement tests, and surveys. Further adding to the utility of this data set, in 2005 the PSID extended the CDS through the Transition to Adulthood Study (TAS) of the original participants, ages 18 and older. The TAS continues to capture additional information, including degree completion, as the initial CDS cohort ages (Institute for Social Research, 2011).

CDS Data Collection

CDS field interviewers collected the majority information through household visits to interview and assess the targeted children and to interview primary caregivers—the individual living in the home who knew the most about the child's activities (Hofferth et al., 1997). For the one-tenth of families who were out of range for in-person interviews, CDS conducted telephone interviews of the primary caregivers without collecting information from the children. Data collected from children included standardized tests and interviews assessing academic ability, self-esteem, and socio-emotional wellbeing. Parent interviews focused on parent literacy, the home environment, children's health and behavior, schooling, childcare history, relationships with absent parents, and food availability. Each primary caregiver also filled out a self-administered household questionnaire with questions about the neighborhood, the household, parenting, family conflict, work schedules, and personal psychological wellbeing. The CDS accommodated parents with specialized literacy or language needs by administering the household questionnaire by phone. After completing the interviews, the CDS gave small amounts of money to the primary caregivers and small gifts to the children.

To gain further information, the CDS mailed questionnaires to the targeted children's elementary or middle school teachers inquiring about the school environment, language ability of the target child, and teacher background. The CDS made two rounds of five reminder calls to non-responding teachers before coding them as non-responses. After completion, interviewers and participants mailed the questionnaires and surveys to the PSID central office where staff coded them and entered them into the data entry program. Quality control measures included double entry verification.

Table 2.

CDS and TAS Data Sets Used in the Current Study

Data set	Year	Participants	Response %
CDS	1997	3,563 children ages 0 to 12 and their primary caregivers	88
		1,109 teachers	52
CDS	2002	2,907 returning children ages 5 to 18 and their primary caregivers	84
		699 teachers	54
TAS	2005	745 former CDS ages 18 and up	89
CDS	2007	1,506 returning children ages 10 to 18 and their primary caregivers	90
TAS	2007	1,118 former CDS ages 18 and up	90
TAS	2009	1,797 former CDS ages 18 and up	92
TAS	2011	1,907 former CDS ages 18 and up	92

(Hofferth et al., 1997; Institute for Social Research, 2008; 2009a; 2009b; 2010; 2011; 2012; 2013)

CDS Population

The current study's population included the original pool of 3,563 CDS children. The analysis for each research question drew differing smaller samples from the overall group, depending upon the specifications of the question at issue and the scores available from the respondents in the targeted years. Table 2 shows the three CDS and four TAS waves of data used in the current study. Response rates were particularly high for the

TAS and for the CDS children and their parents, but response rates were closer to 50% for the teachers.

Research Design

The current study design partitioned low-income individuals into groups based on their academic trajectories and identified factors that determined group membership (Martin & Marsh, 2009; Masten, 2001). The research design was a modified form of Borman and Overman's (2004) two-phase, person-centered study of resilience in mathematics among poor, minority students that was, in turn, based on Finn & Rock's (1997) study of academic success among low-income, minority students. The findings of both studies (Borman & Overman, 2004; Finn & Rock, 1997) were limited by their low-level benchmarks for academic success.

In light of prior studies' limitations related to income and academic competence criteria, the current study's research design (Table 3) first focused on developing benchmarks for accurately identifying a low-income, academically successful sample. Because the literature theorized that low-income status serves a proxy for direct risk exposure (Felner et al., 1995; Sameroff et al., 1993), the efficacy of the low-income benchmark depended upon its ability to distinguish a level of income that included a high proportion of students who had been exposed to the elevated risk levels that threaten degree completion. To answer the first research question, the study used logistic regression to uncover the association between cumulative risk exposure and the odds of postsecondary degree completion, thus determining an elevated level of risk. Addressing the second research question, the research design used an Analysis of Variance test (ANOVA) to determine the mean level of income associated with the elevated risk level, thus establishing the low-income benchmark. The study then returned to logistic regression to answer the third research question associating mathematics and reading performance with students' likelihood of postsecondary degree completion. The results of the mathematics and reading regressions determined the academic success benchmark by indicating a level of prior achievement correlated with higher odds of degree completion.

Table 3.

Research Design

Question	Purpose	DV	IV	Procedure
1	Identify elevated risk level	Postsecondary Degree Completion	Risk Exposure	Logistic regression
2	Identify low-income benchmark	Income	Risk Exposure	ANOVA
3	Identify academic success benchmark	Postsecondary Degree Completion	Mathematics & Reading Achievement	Logistic regression
4	Identify characteristics associated with academic success	- Math Self-Efficacy - Positive Behaviors - Reading Self-Efficacy - Self-Esteem - Family Reading - Parent Expectations - Parental Warmth - Extracurricular Activities - School Connectedness - School Safety - Supportive Friends	Resilience Group	MANOVA ANOVA Discriminant Analysis

Note. DV= dependent or outcome variable. IV = independent or grouping variable.

After developing the benchmarks, the study identified a sample of low-income, academically successful students from the CDS population, placing them into one of three groups: Persistent-Resilient, Improved-Resilient, or Non-Resilient. The group labels mirrored Wyner et al.'s (2007) language from a study that examined three potential trajectories for academically successful students: (a) persistently high achievers, (b) formerly lower achieving students who improved to high achievement, (c) and formerly high achieving students who declined to lower achievement. The design limited the analysis to students who had at some point demonstrated academic success to control for factors unrelated to academic resilience that may contribute to pervasive low achievement, such as significant learning disabilities or low cognitive aptitude. Therefore, instead of defining non-resilient students as those who failed to demonstrate academic success at any point, the design used similar methodology to Reis et al. (2005), who defined non-resilience as prior academic success followed by lower performance.

The final stage of the study was devoted to answering the fourth research question. In this stage, the study used MANOVA and ANOVA tests to identify significant individual, family, and school characteristics related to individuals' resilience group status. The study investigated the individual characteristics of (a) math self-efficacy, (b) positive behaviors, (c) reading self-efficacy, and (d) self-esteem; the family characteristics of (a) family reading encouragement, (b) parent educational expectations, and (c) parental warmth; and the school characteristics of (a) extracurricular activities (b) school connectedness, (c) school safety, and (d) supportive peers. As a final step, the study used discriminant analysis to determine a combination of significant individual, family, and school characteristics that best distinguished between Persistent-Resilient, Improved-Resilient, and Non-Resilient individuals.

Variables

The PSID, CDS, and TAS served as the data sources for all variables. For some variables, the data were used with minor recoding. For others, a number of PSID variables were aggregated to form a single variable. The follow section lists the variables in order of their use in the study and describes how each variable was constructed.

Postsecondary Degree Completion

Research Questions 1 and 3 used Postsecondary Degree Completion as the dependent variable. The research design constructed the Postsecondary Degree Completion variable using data from the TAS surveys where former CDS participants reported their current educational attainment (Institute for Social Research, 2011). The research design relied on all four of the TAS waves to capture the degree completion data for students with the opportunity to complete at least four years of postsecondary education by the final 2011 TAS wave, as shown in Figure 1. Cases were included if one or more of the following were present:

- A positive score for degree completion at any TAS wave
- Scores for at least three consecutive TAS waves
- A score for at least one TAS wave four years postsecondary, as determined by the1997 grade level (Grade 2 and above) or 2002 grade level (Grade 7 and above)

Consequently, a number of CDS participants were excluded from the analysis because they were too young to have completed four years of postsecondary education.

All postsecondary degree completion was treated alike due to the current study's focus on educational attainment beyond a high school diploma as a minimum standard for later economic success (Baum et al., 2013; DeNavas-Walt & Proctor, 2014), rather than an exploration of the efficacy of various types of degrees. Therefore, I converted postsecondary degree completion as reported in the participants' latest year of TAS participation to a dichotomous outcome variable, scoring 1 for an associate's, bachelor's, or graduate degree and 0 for no degree.

Grade at Each Wave					
CDS 1997	CDS 2002	TAS 2005	CDS & TAS 2007	TAS 2009	TAS 2011
7	12	PS3	PS5	PS7	PS9
6	11	PS2	PS4	PS6	PS8
5	10	PS1	PS3	PS5	PS7
4	9		PS2	PS4	PS6
3	8		PS1	PS3	PS5
2	7		12	PS2	PS4
1	6		11	PS1	PS3
K	5		10		PS2

Figure 1. Students with the opportunity to complete four years of postsecondary education by the TAS 2011 wave. Darker cells indicate four or more years post high school. PS = postsecondary year, (e.g., PS1 indicates one year past Grade 12),

Risk Exposure

Question 1 used Risk Exposure as the independent variable. Due to evidence that the numerous proximal risks associated with childhood poverty have additive effects, the research design incorporated multiple risks into a simple event count (Evans & Kim, 2010; Gutman et al., 2002; Sameroff et al., 1993). An event count creates a measure of cumulative risk by summing dichotomous sub-variable outcomes where 0 represents *no risk* or *moderate risk* and 1 represents *high risk*. The simple event count method for establishing levels of cumulative risk had the benefit of representing a large number of risk factors while reducing error from the presumed covariance between the respective risk factors (Evans, 2003; Evans & Kim, 2010). Although some researchers have instead used a weighted risk model, (e.g., Greenberg et al., 1999; Rouse & Fantuzzo, 2009)

Dawes and Corrigan (1974) have recommended using unweighted models, such as event counts, due to their higher consistency over repeated applications.

To develop the Risk Exposure event count, I used CDS data and information from the 1997 and 2002 waves and the primary caregiver files from the eight PSID waves from 1992 to 2002 (Hofferth et al., 1997; Institute for Social Research, 2010; 2012; 2014). The eight PSID waves encompassed the entire lifetime of the younger participants but did not include the preschool years of the oldest participants. The research design used the same risk exposure range for all individuals to prevent the older ones from having higher risk counts simply due to additional time.

I constructed the Risk Exposure variable from nine risk sub-variables, as listed in the following paragraphs. Each sub-variable had prior significant associations with poverty and negative developmental outcomes in children, as discussed in Chapter 2. Unlike several studies that have mixed distal and proximal risk factors together in their analyses (e.g., Burchinal et al., 2008; Gutman et al., 2002), the current study focused only on proximal risks and excluded distal statistical risks, such as maternal education, to limit the analysis to direct risk exposure. For variables where researchers have documented that simple exposure is problematic for children, such as Poor Child Health, I coded all individuals who experienced the risk as a 1. For continuous variables where the level of risk is dependent upon the severity of the condition, such as Insufficient Cognitive Stimulation, I coded all individuals with scores beyond a previously established statistical cutoff as a 1 (Evans & Kim, 2010; Sameroff et al., 1993). The study calculated the Risk Exposure variable for all individuals with at least 75% of the sub-variables present. Likewise, each sub-variable also required at least 75% of the data present to be included for an individual. With each sub-variable counted equally as one exposure, the Risk Exposure variable had a potential range from 0 to 9.

Family Conflict. The CDS modeled questions on the National Survey of Families and Households (Sweet, Bumpass, & Call, 1988), asking parents to indicate whether they used certain methods of conflict resolution among family members, such as frequent fighting, throwing things, and hitting. Questions were scored on a scale from 1 (agree) to 4 (disagree). In 2002 CDS reversed the scale, necessitating reverse coding for the 2002 data. Family Conflict was counted as an event if the score was in the bottom quartile in 1997 or 2002, (Sameroff et al., 1993, p. 84).

Family Upheaval. Parents indicated in the main PSID interviews whether in the past year there had been a family composition change in head of household or wife/partner due to death, institutionalization, or leaving the household. Family upheaval was counted as an event for any affirmative response from 1992 to 2002 (Frisco, Muller, & Frank, 2007).

Food Insecurity. The PSID created questions based on the U.S. Food Security Scale (Cronbach's α = .86 to .93; Carlson et al., 1999), which is a Rasch measurement with questions ordered by severity level. Parents responded to a series of questions regarding their experiences with inadequate food intake during the past year in terms of quantity, quality, and hunger. Food Insecurity was reported only in 1999 using a 4-level categorical scale. The final level was indicated when respondents gave at least two positive responses in any one category and positive responses to all of the questions in the categories below. Food Insecurity counted as an event if CDS reported the family status in the *intermediate* or *severe* ranges (Carlson et al., 1999).

Housing Instability. The CDS modeled housing questions on the National Longitudinal Study of Youth Assessment, asking whether the family had moved to a cheaper residence, moved in with others, or sent the children to live elsewhere due to financial difficulties. Housing Instability was counted as an event if any one of the questions had an affirmative response in 1997 or 2002 (Rouse & Fantuzzo, 2009).

Insufficient Cognitive Stimulation. The CDS used the Caldwell and Bradley HOME Inventory (Kuder-Richardson 20 r = .44 to .88; Bradley & Caldwell, 1984), which incorporated both parent responses and interviewer observations to assess the interactions between the child and primary caregiver on 14 items related to cognitive stimulation. Scores ranged from 1 (never) to 5 (often), but CDS recoded individual items into dichotomous variables and summed them to create a subscale for cases where no more than one item was missing. Insufficient Cognitive Stimulation was counted as an event if the score was in the lowest quartile in 1997 or 2002 (Moore, 1995, p. 78).

Insufficient Emotional Support. The CDS used the Caldwell and Bradley HOME Inventory (Kuder-Richardson 20 r = .44 to .88; Bradley & Caldwell, 1984), which used both parent responses and interviewer observations to assess the interactions between child and primary caregiver on 11 items related to socioemotional support. Sample items included how often the caregiver conversed with, praised, or showed physical affection to the child. Scores ranged from 1 (never) to 5 (often). CDS recoded individual items into dichotomous variables and summed them to create a subscale for cases where no more than one item was missing. Insufficient Socioemotional support was counted as an event if the score was in the lowest quartile in 1997 or 2002 (Moore, 1995, p. 78).

Parental Stress. CDS modeled its Aggravation Scale on the one developed for the Job Opportunities and Basic Skills Training Program (JOBS) baseline evaluation (Cronbach's $\alpha = .69$; Moore, 1995, p. 42). The Aggravation Scale score was developed from parent responses to seven questions that determine parental stress as a result of changes in employment, income, and other factors. Parental Stress was counted as an event if the score was in the top quintile (3 or above) in 1997 or 2002 (LeCuyer-Maus, 2003, p. 138).

Parental Psychological Distress. The CDS used the Kessler 6 Nonspecific Psychological Distress for Primary Caregivers (Kessler et al., 2002) to discriminate cases of parental psychological distress from their responses to six questions regarding their feelings (e.g., sad, nervous, hopeless) in the past four weeks on a scale from 1 (none of the time) to 5 (all of the time). Results were summed to create a scaled score with a maximum of 24. Parental Psychological Distress was counted as an event if in either 1997 or 2002 the parent's score was 13 or above, which is the established benchmark for elevated levels (Kessler et al., 2002).

Poor Child Health. The CDS modeled three questions on the National Health Examination Survey of 1995, asking parents to indicate whether the child had physical or mental conditions that limited play, school attendance, or schoolwork. Poor Child Health was counted as an event if any one of the questions had an affirmative response in 1997 or 2002, (Crump et al., 2013).

Family Income

Research Question 2 required a measure of total family income as the dependent variable and Question 4 used family income for sample selection. The CDS reported total family income for the years 1997, 2002, and 2007 (Institute for Social Research, 2014). The family income variable combined self-reported income from all adults living in the household during the previous year. Not only did PSID Family Income include taxable income, government transfer income, and Social Security income, it also subtracted financial losses, potentially resulting in negative values and zero amounts. The current study used the CDS Family Income data without recoding.

Mathematics and Reading Achievement

Research Question 3 used Mathematics and Reading Achievement as independent variables and Question 4 used one of the academic achievement variables for sample selection. The Mathematics and Reading Achievement variables were individual test results from the Woodcock-Johnson Pscyho-Educational Battery-Revised (Schrank, McGrew, & Woodcock, 2001). The Woodcock-Johnson is a nationally normed assessment of academic achievement in reading and mathematics, designed for use with respondents aged 2 to 90 years of age, using basal and ceiling criteria for varying ability levels. The Woodcock-Johnson constructs standardized scores from raw scores to enable cross-test vertical comparisons and to determine age- or grade-based percentile ranks. The Woodcock-Johnson has been widely used by educators and psychologists for determining achievement levels in school-aged children and its median reliability coefficients and standard errors of measurement for the subtests are strong (Letter-Word, $r = .94$, $SEM = 3.81$; Passage Comprehension $r = .88$, $SEM = 5.12$; Applied Problems $r = .93$, $SEM = 4.08$; Schrank et al., 2001) and well above the range of 7.0 to .80 typically accepted in the social sciences (Nunnally & Bernstein, 1994).

The CDS administered the Woodcock-Johnson to individuals at each five-year interval, using the Letter-Word Identification and Passage Comprehension subtests to assess Broad Reading and using the Applied Problems subtest to assess achievement in mathematics (Institute for Social Research, 2010; 2012). To accommodate individuals whose primary language was Spanish, the CDS used the Spanish version of the assessments. The current study used the CDS Broad Reading and Applied Problems standard scores and percentile ranks with minimal recoding to remove non-score values.

Individual, Family, and School Characteristics

The Question 4 research design included Individual, Family, and School dependent variables with evidence of prior positive association with academic achievement or academic resilience, as discussed in Chapter 2. The Individual, Family, and School Characteristics categories included the 11 individual variables listed in the following paragraphs. Before including the variables, I assessed whether they each represented distinct constructs by checking that their collinearity levels were within acceptable margins, (i.e., $r < .80$; Stevens, 2009). For the 11 variables, Pearson's correlations determined that the collinearity ranges were acceptable for within the Individual ($r = .062$ to $.224$), Family ($r = .117$ to $.334$), and School ($r = -.009$ to $.241$) categories.

To construct the individual variables, I recoded the CDS data to remove non-score values and summed sub-variables into a single score for each CDS wave, when appropriate. As a result, some individuals had scores from as many as three CDS waves for a single variable, necessitating either aggregation of the scores into one score or choosing between the scores. To maximize the potential that each variable would reflect the conditions that led to subsequent achievement, the research design used the score from the earliest data point available for each individual. The sole exception to this methodology was construction of the Extracurricular Activities variable, which used the latest data point because school-based participation in extracurricular activities may be more prevalent in older children and adolescents (Copperman & Bhat, 2007; Mahoney, Larson, Eccles, & Lord, 2005).

Mathematics Self-Efficacy (Individual). In 1997, 2002, and 2007 the CDS determined self-efficacy in mathematics based on child responses to a series of 10 questions regarding how important they perceive math to be, interest in and enjoyment of mathematics, and self-assessment of skill levels relative to peers. Response choices ranged from 1 (low) to 7 (high). Mathematics Self-Efficacy scores reflected the mean of the 10 items.

Positive Behaviors (Individual). In 1997, 2002, and 2007 the CDS assessed participants using the Positive Behavior Scale (r = .82; Polit, 1998). The scale was constructed from primary caregiver responses to a series of 10 questions related to compliance, social competence, curiosity, and self-reliance. Parents were asked if statements apply to their child with responses ranging from 1 (not at all like my child) to 5 (totally like my child). The Positive Behavior Scale scores reflected the mean of the 10 items.

Reading Self-Efficacy (Individual). In 1997, 2002, and 2007 the CDS determined self-efficacy in reading based on child responses to a series of 10 questions regarding how important they perceive reading to be, interest in and enjoyment of reading, and self-assessment of skill levels relative to peers. Response choices ranged from 1 (low) to 7 (high). The Reading Self-Efficacy scores reflected the mean of the 10 items.

Self-Esteem (Individual). In 1997, 2002, and 2007 the CDS used the Rosenberg Self-Esteem Scale (Cronbach's α. = .88 to .90; Robins, Hendin, & Trzesniewski, 2001) to create Global Self Concept Scale scores. Due to a change in the scale after 1997, the current analysis used only the 2002 and 2007 data. Children responded to nine questions related to how well they do things, how others perceive them, and whether they like themselves. Scores were the mean of responses ranging from 1 (not very true of me) to 5 (very true of me).

Family Reading (Family). In 1997, 2002, and 2007 the CDS asked primary caregivers questions from the Caldwell and Bradley HOME Inventory (Bradley & Caldwell, 1984). Scores were based on responses to three questions regarding parent and child reading frequency from 1 (never) to 6 (every day), and number of books in the house from 1 (none) to 5 (20 or more). Responses were summed to create a reading scale with a maximum score of 17.

Parent Expectations (Family). In 1997, 2002, and 2007 the CDS assessed parental expectations using a question based on the NELS:88. Primary caregivers responded to the question by designating the amount of education they expected their child to achieve based on a scale from 1 (11^{th} grade or less) to 8 (doctoral degree).

Parental Warmth (Family). In 1997, 2002, and 2007 the CDS used the Parental Warmth scale from the JOBS evaluation (Moore, 1995, p. 42) to assess parental warmth. Scores were calculated from interviewer observations assessing six items of parent-child interaction during a home interview, including parental tone of voice and use of praise.

Scores ranged from 1 (often) to 5 (never). The CDS recoded individual items into dichotomous variables and summed them to create a subscale for cases where no more than one item was missing.

Extracurricular Activities (School). In 2002 and 2007 the CDS collected information from children and primary caregivers regarding their frequency of playing a musical instrument and their participation in school sports, school clubs, scouts or hobby clubs, and volunteer service activities on a scale from 1 (less than once a month) to 6 (every day), with a maximum potential score of 27 (clubs and volunteer services had a maximum of 5—almost every day).

School Connectedness (School). In 2002 and 2007 the CDS asked children to respond to five items that measured their degree of closeness with teachers and level of participation in class. Scores on each item ranged from 1 (never) to 6 (every day). Responses were summed to create a connectedness score with a maximum value of 30.

School Safety (School). In 1997 and 2002, the CDS surveyed elementary and middle school teachers on eight questions, asking them to judge the severity of specific problems in their schools (e.g., physical conflict, theft, teacher abuse, weapons, and vandalism) on a 0 – 3 scale indicating increasing severity. Responses were summed to determine a cumulative safety score with a maximum value of 24.

Supportive Friends (School). In 2002 and 2007 the CDS asked children questions regarding how often they talked with friends about plans for the future and problems at school. Responses ranged from 1 (never) to 6 (every day), with 7 indicating no friends and reverse scored to 0. Two additional questions asked whether the child's friends thought schoolwork was important and if their friends planned to go to college.

Responses ranged from 1 (none) and 5 (almost all or all). Responses to the four questions were summed to create a cumulative peer score with a maximum value of 22.

Statistical Procedures

The research design relied on four statistical procedures to answer the four research questions: logistic regression, ANOVA, MANOVA, and discriminant analysis. The following section provides justification for the inclusion of each procedure and an explanation of how they were used. Each procedure is listed in order of its use in the study.

Logistic regression

The current study used logistic regression for research Questions 1 and 3 because they required assessment of the degree to which the predictor variables Risk Exposure, Mathematics Achievement, and Reading Achievement contributed to the dichotomous Postsecondary Degree Completion outcome.

The logistic regression model equation is

$$g(x) = ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + \beta_1 x_1$$

where $\pi(x)$ is the predicted probability that $y = 1$, given the values of x (Hosmer, Lemeshow, & Sturdivant, 2013). In logistic regression, the predicted probability is typically reported as a log-odds statistic, or the natural logarithm of the odds, which resembles a linear regression expression. Log-odds were used to calculate natural odds, odds ratios, and predicted probabilities using the following equations:

Odds = $e^{\beta 0 + \beta 1 x 1}$

Odds ratio = $\frac{Odds}{1 - Odds}$

$$\text{Probability} = \frac{Odds}{1 + Odds}$$

To determine the likelihood of degree completion, the current study used the odds ratio, which is the ratio of the odds that *y* will happen given a unit of change in *x,* to the odds of *y* not happening. When the odds ratio is very small (e.g., .0001) the likelihood that *y* = 1, given the value of *x,* approaches impossibility. Conversely, when the odds ratio is very large (e.g. 9999), the likelihood that *y* = 1, given the value of *x,* approaches certainty. An odds ratio of 1 indicates 50:50 odds, or equal likelihood that *y* = 0 or *y* = 1. The research design set the benchmarks for academic achievement and elevated risk exposure at the points where the odds ratios rose above 1.0, similar to the methodology used by Adelman (2006) in his study using high school coursework to predict degree completion (p. 31). The current study aimed for an odds ratio of 1.2 to maintain adequate statistical power as determined *a priori* by G*Power 3.1 (assuming $\alpha = .05$, one-tailed, and a sample size of 1,300).

ANOVA

Research Questions 2 and 4 used ANOVA tests to distinguish meaningful differences between groups. ANOVA tests use calculations of population variances to determine if differences between group means indicate samples were taken from differing populations or if they were more likely due to the normal distribution of scores from a single population. The ANOVA model rests on a number of assumptions, including normality of the sampling distribution and homogeneity of variance (Hallahan & Rosenthal, 2000; Howell, 2011), which is of importance to the current study that had a few skewed variables due to oversampling low-income families and parental warmth scores. The current study also had unequal group sizes that could have potentially influenced within-group variance. Despite these limitations, ANOVA was still an appropriate choice because, according to Howell (2011), ANOVA is “robust with respect to violations of the assumptions of normality and homogeneity of variance” (p. 411), particularly when the sample sizes are greater than 30 (Hallahan, 2000). Given the limitations of the current study’s data, I chose to ensure the accuracy of the statistical testing by using the Games-Howell follow-up test because researchers have found it to be accurate despite unequal group sizes and unequal variances, particularly with groups larger than 50 (Games, Keselman, & Rogan, 1981).

MANOVA

Although Questions 2 and 4 used ANOVA tests to analyze group differences, MANOVA was an appropriate added step for the fourth research question because it investigated the association of 11 dependent variables with Resilience group status. MANOVA allows for the simultaneous analysis of multiple dependent variables, while avoiding the risk of an increased Type 1 error rate that accompanies multiple separate ANOVAs. The use of MANOVA also bypasses the loss of statistical power that would accompany a proportional reduction in α to accommodate numerous ANOVA tests (Stevens, 2009). Because dependent variables considered together should be correlated and share a conceptual meaning, the current study’s research design analyzed Individual, Family, and School characteristics in three separate MANOVAs.

Question 4 was solely concerned with the main effects related to Resilience group status, but the wide age range of the individuals in the CDS sample presented a potential threat to the study if the effects of any characteristics were to differ for older and younger students. To account for the participants’ school levels, the research design utilized a 2 x

3 factorial MANOVA design comparing low-income Persistent-Resilient, Improved-Resilient, and Non-Resilient students at both Middle School and High School levels. (I coded individuals who were in Grades 6, 7, or 8 in 2002 or 2007 as Middle School and students who were in Grades 9, 10, 11, or 12 in 2002 or 2007 as High School). The three factorial MANOVAs investigated the main effect of Resilience status, as well as the potential interaction of Resilience status and School Level, determining (a) whether the Individual, Family, and School characteristics of Sustained-Resilient, Improved-Resilient, and Non-Resilient students differed; and (b) which, if any, of the Individual, Family, and School characteristics were more important predictors of resilience at the middle and high school levels.

The MANOVA model rests on assumptions of univariate normality, multivariate normality, and homogeneity of covariance matrices (Stevens, 2009). Because I anticipated potential issues with normality, I interpreted the MANOVA results using Pillai's Trace because it is the statistic most robust to violations (Stevens, 2009). When a MANOVA test indicated significant group differences, I conducted ANOVA and Games-Howell follow-up tests to determine which specific variables and Resilience groups differed.

Discriminant Analysis

As a final step in answering research Question 4, the study design used discriminant analysis to determine how combinations of variables distinguished between Persistent-Resilient, Improved-Resilient, and Non-Resilient students. Although ANOVA and follow-up tests provide information on individual variables of interest, discriminant analysis considers variables in combination and quantifies the extent each variable contributes to group membership. The research design included a discriminant analysis using the significant Individual, Family, and School characteristic variables identified by the prior ANOVA tests. Because the literature suggested that non-resilient students may have had higher levels of direct risk exposure (Gutman et al., 2002), the analysis also included the cumulative Risk Exposure variable.

Discriminant analysis identifies unique, uncorrelated linear combinations of the variables that best discriminate among the resilience groups, also known as *discriminant functions* (Stevens, 2009). With three resilience groups, discriminant analysis had the potential to create up to two significant discriminant functions. The equation for discriminant analysis is

$$D = g_1Y_1 + g_2Y_2 + . . . + g_pY_p$$

D represents a discriminant function, while p represents the number of continuous predictors and g represents the discriminant weights. In discriminant analysis, Wilks' λ determines which functions are significant and eigenvalues indicate the percent of variance explained by each function. Because discriminant analysis is a mathematical maximization procedure, the analysis accounted for unequal group sizes when computing probabilities.

For significant discriminant functions, analyses of the function correlations and standardized coefficients determine whether the function is meaningful or interpretable. Consequently, the interpretation of discriminant functions involves some subjectivity and depends on general knowledge of the underlying constructs under study (Silva & Stam, 1995). Function correlations in the structure matrix above the threshold of .3 indicate a high correlation with the function (Stevens, 2009). Similarly, standardized coefficients in the pattern matrix below .3 indicate variables are redundant in the function and are not necessary. Finally, to test the significance of the group differences suggested by the discriminant function, I ran ANOVA and Games-Howell *post hoc* tests on the discriminant scores.

CHAPTER 4

Results

Chapter 4 is organized into four sections, each devoted to one of the four research questions. Each section begins with simple descriptive statistics for the variables and a comparison of the question's sample with the wider CDS population. Following the report of results from the statistical analyses, each section concludes with a brief discussion of the findings as they relate to the research question at issue.

Question 1

What level of cumulative risk exposure is associated with postsecondary degree completion? The Question 1 analysis relied on logistic regression tests with Risk Exposure scores predicting the odds of Postsecondary Degree Completion. The purpose of the logistic regressions was to indicate a level of elevated risk where degree completion rates reached unlikelihood in the CDS sample. The elevated risk level determined by the Question 1 analysis then served as a key variable in answering the second research question.

Outcome Variable

The dichotomous outcome variable for the first research question was Postsecondary Degree Completion with 0 indicating no degree and 1 indicating that an associate's, bachelor's, or graduate degree had been obtained. I constructed the Degree Completion variable using TAS data from the 2005 to 2011 waves, as described in Chapter 3. Table 4 shows that degree completion information was present for 38% of the CDS population. The remaining 62% were lost from the sample because adequate degree information was missing for approximately one-third of the participants and the remaining quarter of the participants were too young to have completed four years of postsecondary education before the final TAS wave. Overall, 31% of the available CDS sample obtained postsecondary degrees.

Table 4.

Distribution of the CDS Postsecondary Degree Completion Variable Compared With the National Population

CDS	%	n
Degree information missing	38	1,371
Less than 4 years postsecondary	23	828
Degree information present	38	1,364
No degree	69	947
Degree obtained	31	417
Associate's	7	98
Bachelor's	21	285
Master's	2	24
Doctorate	< 1	10
National		
Associate's	8	
Bachelor's	26	
Master's/Doctorate	7	

Note. National statistics from 2012 (NCES, 2013d; 2013e).

In light of the substantial amount of missing data, I compared the CDS degree completion rates with similar national statistics from 2012 for individuals aged 25 to 29 (NCES, 2013d; 2013e). The comparison revealed that the CDS degree attainment rates for associate's degrees were similar to the national attainment rates, but bachelor's and graduate degrees were lower. Nationally, 41% of young adults had obtained postsecondary degrees in 2012 compared with 31% in the CDS sample during a similar period of time. The lower degree attainment rates in the CDS sample may be attributed to the substantial number of missing scores, the PSID oversampling of low-income families

(Institute for Social Research, 2013), or methodology that missed younger individuals in the sample who may take more than four years to complete degrees

Table 5.

Risk Exposure Missing Data, Individuals with Elevated Risk, and Correlations with Risk Exposure Scores by Sub-Variable

	Present		Elevated Risk		
Sub-Variable	%	n	%	n	*r*
Family Conflict	80	2,854	26	729	.357*
Family Upheaval	89	3,173	49	1,746	.537*
Food Insecurity	100	3,563	3	101	.074*
Housing Instability	91	3,234	10	308	.366*
Low Cognitive Stimulation	100	3,563	34	1,220	.407*
Low Emotional Support	100	3,563	23	833	.455*
Psychological Distress	90	3,221	4	144	.207*
Parental Stress	91	3,243	2	1,023	.447*
Poor Child Health	100	3,563	10	339	.249*

* $p < .05$

Predictor Variable

Question 1 used Risk Exposure as the predictor variable. Risk Exposure consisted of a cumulative risk count of nine sub-variables representing events or conditions associated with both low-income status and poor developmental outcomes in children. Table 5 shows that the nine risk sub-variables had between 80% and 100% of data present. Pearson's correlations indicated that each sub-variable significantly contributed to the overall risk scores, ranging from the more weakly correlated Food Insecurity *(r* = .074) to the strongly correlated Family Upheaval (r = .537). Although Risk Exposure scores potentially ranged from 0 to 9, the actual score distribution in the Question 1 sample ranged from 0 to 6 with a mean of 1.53, a median of 2, and an *SD* of 1.17. The

Risk Exposure variable had a relatively normal distribution with skewness and kurtosis levels within the -2.0 to 2.0 range (Lomax & Hahs-Vaughn, 2012).

Table 6.

Distribution of the Question 1 Sample Compared With the CDS Population

	CDS Population		Q1 Sample	
Criteria	%	n	%	n
Total	100	3,563	37	1,329
Sex*				
Male	51	1,813	47	628
Female	49	1,750	53	701
Race/Ethnicity*				
White	46	1,642	47	624
Black	41	1,455	43	570
Hispanic	8	267	6	78
Asian	2	64	1	13
Am. Indian	1	19	0	5
Other	3	108	3	35
1997 Income Quintile*				
1 < $14,676	20	713	17	231
2 < $27,800	20	715	19	253
3 < $43,220	20	710	19	250
4 < $65,000	20	716	21	282
5 > $65,000	20	709	24	313
1997 Mathematics Quintile*				
1 < 20^{th}	14	317	10	107
2 < 40th	16	348	14	153
3 < 60th	20	443	19	211
4 < 80th	19	410	19	207
5 > 80th	31	691	38	414
Risk Exposure Score*				
0	14	469	20	266
1	29	992	33	442
2	30	1,013	28	371
3	18	610	13	173
4	7	252	5	60
5+	3	81	1	17

Note. Mathematics and Risk Exposure n < 3563.
* $p < .05$

Sampling

The sample for Question 1 included the 1,329 individuals from the CDS population with scores for both Postsecondary Degree Completion and Risk Exposure. As illustrated in Table 6, chi-square analyses found that Question 1 sample was disproportionally female, Black, higher income, higher performing in mathematics, and exposed to fewer risks than the excluded group. The sample's greater percentage of higher income and higher achieving individuals was most likely to bias the Question 1 analysis through an elevated degree completion rate. However, the CDS degree completion rate was well below the national level (NCES, 2013d; 2013e), making loss of non-degreed individuals of lesser concern. Although very high-risk individuals are less likely to be academically successful (Gutman et al., 2002; Robinson et al., 2002; Rouse & Fantuzzo, 2009), and thus less likely to complete degrees, the sample's loss of a large proportion of this small group afforded the potential to bias the results only if an unexpected number of the missing individuals had obtained degrees.

Results of Statistical Analyses

The Question 1 analyses used logistic regressions with Risk Exposure levels predicting the odds of Postsecondary Degree Completion. The logistic regression equation was

$$\hat{g}\,(DEGREE) = \hat{\beta}_0 + \hat{\beta}_1\text{RISK}.$$

The null hypothesis was that there was no relationship between Postsecondary Degree Completion and Risk Exposure,

H_0: $\beta_1 = 0$.

Main sample. The main analysis was a logistic regression test using the entire sample of the 1,329 CDS individuals for whom data was present. The Likelihood-ratio test indicated that the Risk Exposure model fit the data significantly better than the empty model, $\chi^2 = 67.693$, $p < .001$($\alpha = .05$, two-tailed), and the Hosmer and Lemeshow test of goodness of fit also indicated that the model adequately fit the data, $\chi^2(3) = 6.602$, $p = .086$. The classification table showed that the model correctly classified 69.3% of cases.

Table 7.

Odds and Probability of Degree Completion for Each Level of Risk Exposure

Risk Exposure	Odds	Odds Ratio	Probability
0	.841	5.295	45.7%
1	.533	1.142	34.8%
2	**.338**	**.510**	**25.3%**
3	.214	.273	17.6%
4	.136	.157	12.0%
5	.086	.094	7.9%
6	.055	.058	5.2%
Actual CDS degree completion	.443 (408:921)	.795 (.443/.557)	30.6% (921/1329)

Note. Bold text indicates the level of elevated risk exposure.

The regression yielded the log-odds statistics of $\beta_0 = -.173$ ($SE = .097$) and $\beta_1 = -.456$ ($SE = .059$), which I used to calculate the odds of degree completion for each level of Risk Exposure with the equation ODDS = $\boldsymbol{e}^{-.173\ -\ .456(RISK)}$. Table 7 shows the resulting odds and probabilities for each level of Risk Exposure. The odds ratio rose above the 1.0 threshold at a Risk Exposure level of 1, thus, a Risk Exposure level of 2 indicated elevated risk and lower than average odds of degree completion. Because the Risk Exposure variable included count data with only whole number values, the ideal odds ratio of 1.2 was not obtainable. Given the conditions of the logistic regression ($\alpha = .05$, one-tailed, n = 1,329, achieved odds ratio of 1.142), *post hoc* statistical power analysis determined that the probability of correctly rejecting the null hypothesis was .78, which is just below the ideal power of .80 (Cohen, 1992).

Race and ethnicity samples. Because the literature suggested potential differences in the effects of poverty on individuals of various racial and ethnic backgrounds (e.g., Burney & Beilke, 2008; Coleman, 1966; Orefield & Lee, 2005), I also ran logistic regression tests on homogeneous samples by race and ethnicity. The Hispanic sample was too small (n = 78) to obtain adequate statistical power and the Black and White samples' Hosmer and Lemeshow tests both indicated poor model fit (p = .005 and .034, respectively). However, when aggregating the underrepresented minority groups of American Indian, Black, Hispanic, and Other together (n = 688) the model fit was significant, $\chi^2 = 7.260$, $p < .001$, and the Hosmer and Lemeshow test also indicated that the model adequately fit the data, $\chi^2(3) = 7.260$ 3, $p = .064$. The classification table showed that the model correctly classified 80% of cases.

Table 8.

Odds and Probability of Degree Completion for Underrepresented Minorities at Each Level of Risk Exposure

Risk Exposure	Odds	Odds Ratio	Probability
0	.479	.918	32.4%
1	.318	.466	24.1%
2	.211	.268	17.4%
3	.140	.163	12.3%
4	.093	.103	8.5%
5	.062	.066	5.8%
6	.041	.043	4.0%
Actual CDS degree completion	.443 (408:921)	.795 (.443/.557)	30.6% (921/1329)

After inserting the underrepresented minority log-odds statistics, the resulting equation for the odds of degree completion was ODDS = $\boldsymbol{e}^{-.737\ +\ -.409(RISK)}$. The calculated odds and probabilities of degree completion for underrepresented minorities are shown in Table 7. In contrast to the larger CDS sample, no level of risk exposure for underrepresented minorities rose above an odds ratio of 1.0. In fact, the classification table predicted no degree completion for underrepresented minorities.

Although the logistic regression model for White individuals (n = 624) was a poorer fit for the data, for the purposes of comparison, I calculated the odds and probability values using the log-odds statistics generated by the White sample's logistic regression tests, ODDS = $\boldsymbol{e}^{.161\ +\ -.380(RISK)}$. The results, as shown in Table 9, reveal that the odds of degree completion for White individuals at each level of risk exposure were higher than the results of both the heterogeneous sample (Table 7) and the underrepresented minority sample (Table 8). Despite the higher odds in the White sample, the benchmark for elevated risk remained at a Risk Exposure level of 2.

Table 9.

Odds and Probability of Degree Completion for White Individuals at Each Level of Risk Exposure

Risk Exposure	Odds	Odds Ratio	Probability
0	1.175	4.084	54.0%
1	0.803	1.219	44.5%
2	**0.549**	**0.602**	**35.5%**
3	0.376	0.346	27.3%
4	0.257	0.213	20.4%
5	0.176	0.137	14.9%
6	0.120	4.084	0.7%
Actual CDS degree completion	.443 (408:921)	.795 (.443/.557)	30.6% (921/1329)

Note. Bold text indicates the level of elevated risk exposure.

Underrepresented minority status as a risk exposure. The findings related to depressed degree completion in the underrepresented minority sample suggested the potential presence of an unaccounted risk directly or indirectly related to minority status. Unaccounted risks pose a threat to the findings when individual risks scores are erroneously lower than their actual risk levels, biasing the results toward a lower elevated risk exposure level. To determine whether including underrepresented minority status as a risk would change the benchmark, I computed a new Modified Risk variable, which added one additional point to the risk scores of the 52% of the cases (n = 688) with underrepresented minority status. The new Modified Risk variable had a mean of 2.40, a median of 2, and an *SD* of 1.29.

Table 10.

Odds and Probability of Degree Completion for the CDS Sample Including Underrepresented Minority Status as a Risk

Risk Exposure	Odds	Odds Ratio	Probability
1	0.686	2.184	40.7%
2	**0.414**	**0.709**	**29.3%**
3	0.251	0.335	20.1%
4	0.151	0.179	13.2%
5	0.092	0.101	8.4%
6	0.059	0.059	5.3%
Actual CDS degree completion	.443 (408:921)	.795 (.443/.557)	30.6% (921/1329)

Note. 0 Risk Level calculations resulted in odds above 1.0. Bold text indicates the level of elevated risk exposure.

The Modified Risk logistic regression had a slightly better model fit than the original Risk Exposure regression. The omnibus results had a higher chi-square value, $\chi^2 = 109.031$, $p < .001$ and the Hosmer and Lemeshow test had an increased probability, $p = .124$. The model also correctly classified 70.0% of cases—a minor increase of .7%. The correlation between the Modified Risk exposure variable and Degree Completion in the sample was closer to medium (r_{pb} = -.275) than the original Risk Exposure correlation (r_{pb} = -.218). An additional benefit of the Modified Risk score was the increase in statistical power to 1.0 that accompanied the increase in the Odds Ratio threshold to 2.18. Despite the improvements in the model related to the modification of the risk variable, Table 10 shows that the benchmark for elevated risk exposure remained at 2 risks.

Summary of Findings: Answering Research Question 1

Question 1 investigated the levels of cumulative risk exposure associated with higher odds of postsecondary degree completion. The findings indicated that exposure to more than one direct risk factor reduced the odds of degree completion in the CDS sample. Consequently, once individuals reached an elevated direct risk exposure level of 2, their odds of postsecondary degree completion dropped below 50:50 and the probability of degree completion fell below the average degree completion rate.

The direct risks associated with reduced degree completion included a parent exiting the household, food insecurity, housing insecurity, serious child health problems, low cognitive stimulation, lack of emotional support from the primary caregiver, frequent use of violence to settle family conflicts, high parental stress levels, and a parent in psychological distress. The analysis also suggested that underrepresented minority status may have acted as an additional direct or indirect risk factor. However, inclusion of underrepresented minority status as a risk factor did not affect the elevated risk exposure level, which remained at a value of 2.

Further analysis suggests that low-risk individuals in the CDS population were distinct from those with elevated-risk levels in a number of ways, as shown in Table 11.

The low-risk groups had significantly higher math achievement than the elevated-risk groups, as determined by ANOVA and follow-up tests ($p < .001$). Additionally, the degree completion rates for both low risk exposure groups were significantly higher than each of the elevated risk groups ($p < .001$). Although chi-square tests detected no significant group differences by sex, they suggested differences by race and ethnicity, with Black, American Indian, and Other groups more likely to have elevated risk exposures. For a deeper exploration of the risk exposure groups by their differences in income, the statistical analysis turns to Question 2.

Table 11.

Characteristics of Students at Each Level of Risk Exposure

		Low Risk		Elevated Risk		
Measure		0	1	2	3	4 +
Mean 1997 Math Rank		72[a]	63[b]	54[c]	52[c]	46[c]
Degree Completion Rate		.53[a]	.45[a]	.25[b]	.22[b]	.11[c]
Sex	n	%	%	%	%	%
Male[a]	1730	14	28	29	19	10
Female[a]	1687	13	30	30	17	9
Race/ethnicity						
White	1605	19	32	28	14	7
Black	1417	8	24	31	23	14
Hispanic	225	20	36	32	8	4
Asian	41	7	51	20	20	2
Am. Ind.	17	0	18	41	12	29
Other	97	8	29	30	23	11

Note. Within each characteristic, groups with the same superscript were not significantly different from one another.

Question 2

What level of income is associated with elevated proximal risk exposure? The first research question determined that individuals in the CDS sample with an elevated risk exposure of two or more proximal risks had reduced odds of postsecondary degree completion. The second research question explored the level of income associated with elevated risk exposure using ANOVA tests to determine the mean Family Income for each Risk Exposure group. The level of income associated with elevated risk exposure informed the benchmark for selecting the low-income sample used in the fourth research question's analyses.

Table 12.
Comparison of the 1997 and 2002 Family Income Variables

Criterion	1997 Family Income	2002 Family Income
Valid scores	3563	3356
Missing scores	0	207
Range	1 to 700,000	- 49,840 to 1,365,600
Mean	44,539	62,406
Median	34,900	46,000
Standard deviation	43,313	77,230
Skewness	4.71	7.132
Kurtosis	43.650	79.852
Correlation with Risk	r = -.240	r = -.201

Outcome Variable

Family Income served as the outcome variable for Question 2. As described in Chapter 3, the PSID collected Family Income information during their biannual interviews and reported Family Income at each of the three CDS waves —1997, 2002, and 2007. Because the Question 2 analysis needed only one year's data, I eliminated the 2007 wave from consideration due to the high number of students who aged out of the sample before 2007 (n = 1,472). The decision between the 1997 and 2002 waves rested on the amount of missing data, the distribution and variability of scores, and correlation with Risk Exposure. Table 12 compares descriptive statistics for the 1997 and 2002 CDS Family Income data. The analysis indicated the 1997 Family Income variable was superior on each of the comparison criteria because it included all cases, had a more normal distribution, and the 1997 data had a stronger correlation with Risk Exposure, r = -.240. For these reasons, I selected 1997 Family Income as the outcome variable for Question 2.

Grouping Variable

Question 2 analyzed groups of students at varying Risk Exposure levels, with particular interest in the individuals at the elevated benchmark, Level 2. Risk Exposure scores reflected a simple event count of the direct risks Food Insecurity, Housing Instability, Poor Child Health, Family Upheaval, Insufficient Cognitive Stimulation, Insufficient Emotional Support, Family Conflict, Parental Stress, and Parental Psychological Distress, as outlined in Chapter 3. Risk Exposure scores were reported as whole numbers ranging from 0 to 9.

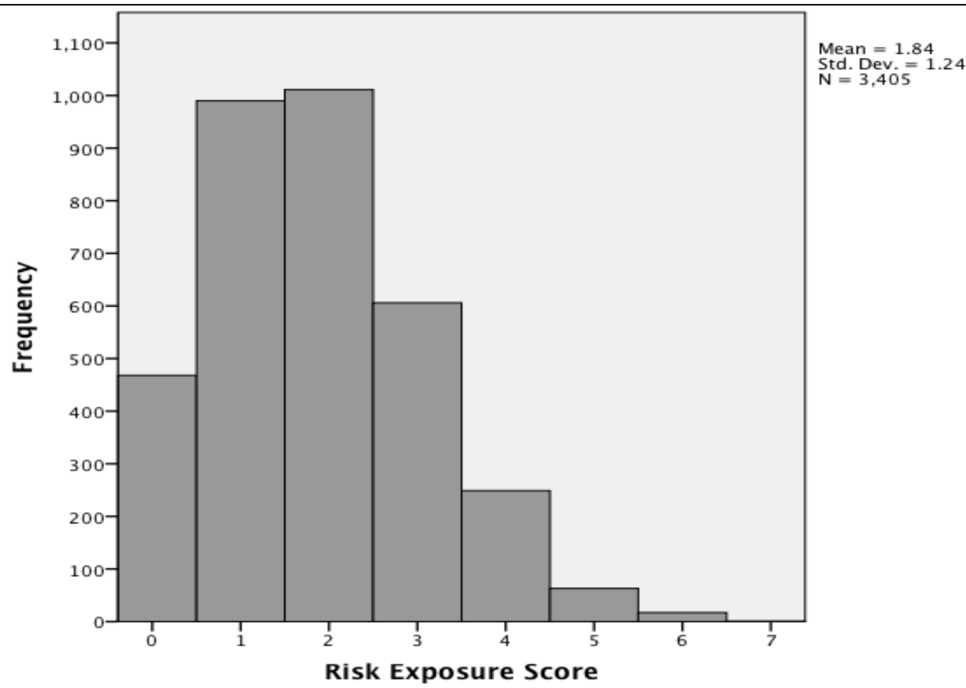

Figure 2. Distribution of Risk Exposure scores in the Question 2 CDS sample

In the Question 2 sample, the actual Risk Exposure scores ranged from 0 to 6 with only 17 individuals at the highest risk level, as shown in Figure 2. To balance the groups for ANOVA testing, I recoded the eight-group Risk Exposure variable into five groups, collapsing the Risk Exposure levels of 4 through 7 together into one group of *4 and above.* This methodology increased statistical power without affecting analysis of the main group of interest—Level 2. Although the group collapse offered some remediation of the uneven group sizes, the resulting Risk Exposure group counts were still unbalanced: Zero – 468, One – 990, Two – 1,011, Three – 606, Four and above – 330.

Sampling

The sample for research Question 2 included all individuals from the CDS population with scores for both 1997 Family Income and Risk Exposure. The resulting sample of 3,405 individuals included 96% of the CDS population. Chi-square analyses determined that data were not missing at random for race/ethnicity and income quintile, with excluded individuals slightly more likely to be in the lowest two income quintiles and of Black, Hispanic, or Asian background. Despite these minor discrepancies, the 96% inclusion rate suggested that the Question 2 sample closely mirrored the distribution of the original CDS sample.

Results of Statistical Analyses

Question 2 used a one-way ANOVA test to determine whether the means of the Risk Exposure levels were significantly different from one-another. The null hypothesis was that all means were equal:

H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$

The specific mean of interest was μ_3, the elevated Risk Exposure threshold of 2. ANOVA results detected at least one significant difference between the means of the Risk Exposure groups $F(4, 3{,}412) = 53.619$, $p < .001$ ($\alpha = .05$, two-tailed). Games-Howell follow-up tests determined that all five Risk Exposure groups were significantly different from one another for all contrasts ($p \leq .001$). *Post hoc* analysis determined that given the listed conditions, the achieved statistical power was acceptable at 1.00 (Cohen, 1992).

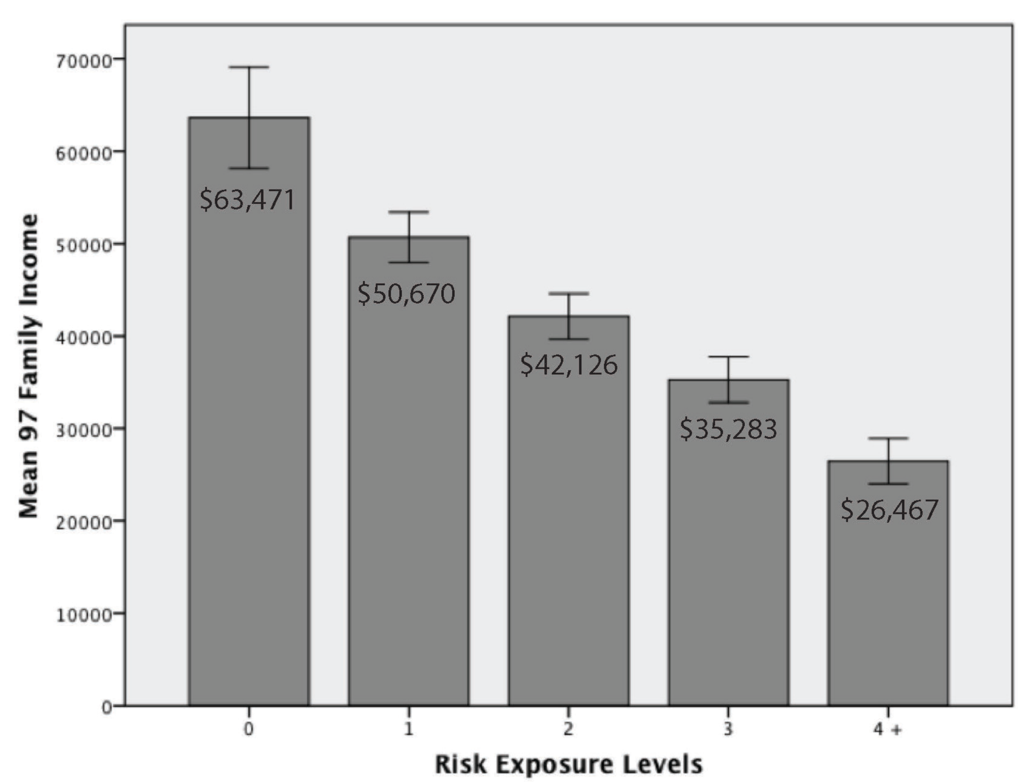

Figure 3. Mean income levels for each risk group with 95% confidence intervals.

Figure 3 shows the means for the five Risk Exposure groups with their 95% confidence intervals indicated by error bars. The mean for the elevated Risk Exposure level of 2 was $42,126 with a confidence interval of $39,655 to $44,597. As levels of

Risk Exposure increased, the income means dropped substantially between 16.2% and 25.0%, or about $10,000 between each level. The greatest drop was between 3 risks and 4 or more risks, most likely attributable to the aggregation of the final group obscuring a more gradual reduction in the means.

Modified Risk analysis. Due to the better Question 1 model fit for the Modified Risk variable that included underrepresented minority status, I also conducted an ANOVA using Modified Risk scores as the grouping variable. ANOVA results indicated the existence of at least one significant difference between the means of the Modified Risk groups $F(4, 3{,}412) = 74.349$, $p < .001$. Games-Howell follow-up tests indicated that all five Risk Exposure groups were significantly different from one another for all contrasts ($p \leq .002$). The Modified Risk elevated Level 2 mean was $44,193, which was higher than the corresponding mean for the original Risk Exposure variable. However, the Modified Risk Level 2 mean had a confidence interval of $41,653 to $46,735, which substantially overlapped the Level 2 confidence interval of the original Risk Exposure variable ($39,655 to $44,597).

Benchmarks. In light of the ANOVA results, I set the 1997 low-income benchmark at $42,126, the mean income level for original Risk Exposure variable level 2, which was more conservative and within the confidence intervals for both risk variables, as described in the previous paragraph. For the 2002 and 2007 benchmarks, I adjusted the 1997 benchmark for inflation using the Bureau of Labor Statistics' (n.d.) CPI Inflation Calculator. The results were a 2002 benchmark of $47,218 and a 2007 benchmark of $54,420. The CPI Inflation Calculator determined that these benchmarks would be the equivalent of $62,452 in 2015.

Summary of Findings: Answering Research Question 2

In the CDS sample, the levels of income associated with the elevated proximal risk exposure Level 2 were $42,126 in 1997, $47,218 in 2002, and $54,420 in 2007. To place the Question 2 low-income benchmarks into context, Table 13 compares them with the CDS Family Income means and medians as well as the national means and medians for the same years. At each wave, the low-income benchmarks fell between the mean and median incomes for both the CDS and the national populations, but in most cases the benchmarks were closer to the medians because high-income outliers tend to skew income means upward. In 1997, the CDS population had lower means and medians than the national figures, but in following years the CDS figures exceeded their national counterparts. This relative increase was most likely due to the restricted ages of the CDS cohort. Although the national means reflected individuals at all stages of their working careers, the CDS cohort was made of parents of young children in 1997 who aged 10 years over the course of the study.

Table 13.

Low-Income Benchmarks Compared with CDS and National Median and Mean Incomes

		CDS		National	
Year	Benchmark	Median	Mean	Median	Mean
1997	$42,126	$34,900	$44,539	$37,005	$49,692
2002	$47,218	$46,000	$62,405	$42,409	$57,852
2007	$54,420	$51,742	$73,281	$50,233	$67,609
Elevated Risk Identification Rate	79%	77%		74%	

Note. National statistics from the U.S. Census Bureau (2014) included income from people 15 years and older in the household.

Efficacy of identifying of elevated risk individuals. The utility of the income benchmarks depends upon their ability to identify a high proportion of individuals with elevated risk exposures. However, because income was not perfectly correlated with risk exposure (r = -.241), any income benchmark was likely to exclude a number of elevated risk individuals. Setting the income benchmark at the mean for two risk exposures excluded the two-exposure individuals above the mean income along with other higher income individuals with elevated risk levels. To determine how well the proposed benchmarks identified individuals with elevated risk levels, I conducted an analysis on the CDS population, finding that the low-income benchmarks identified 1,549 out of 1,956 elevated Risk Exposure individuals—an identification rate of 79%. For Modified Risk the income benchmark showed similar results, identifying 1,923 out of 2,408 elevated risk individuals, or 80%.

Efficacy of alternate benchmarks. As discussed previously, the low-income benchmarks were close to the medians for each wave, which prompted the question of whether median income levels would have provided simpler benchmarks with similar utility. When the benchmarks were reset at the medians for the CDS population, the lower benchmark reclassified 118 individuals as higher income—47 with elevated risk levels—yielding an identification rate of 77%. Similarly, when the benchmarks were set at the national median incomes, 93 of the 213 reclassified individuals had elevated risk levels and the identification rate was 74%. By contrast, using free or reduced National School Lunch Program status to identify low-income individuals detected 1422 of 2408 high-risk individuals or 59%, due to 225 high-risk individuals falling into the full-price lunch category and a substantial lack of participation due to ineligibility or choice. These figures suggest that an income benchmark set at the median for a population is likely to identify about three-fourths of the high-risk individuals, which is only slightly lower than the more complex method of counting proximal risk exposure and setting benchmarks at the mean income of the elevated risk level.

Table 14.
Characteristics of CDS Low-Income Individuals

	Low-Income		Higher Income		All	
Criteria	%	n	%	n	%	n
1997 Wave	59	2,103	41	1,460		3,563
2002 Wave	55	1,948	40	1,408		3,356
2007 Wave	52	1,838	37	1,332		3,170
Ever identified low-income	71	2,538				
Sex						
Male	51	1,283	52	530	51	1,813
Female	49	1,255	48	495	49	1,750
Race/Ethnicity*						
White	37	879	74	763	46	1,642
Black	54	1,273	18	182	41	1,455
Hispanic	9	241	3	26	8	267
Asian	1	37	3	27	2	64
Am. Indian	1	18	0	1	1	19
Other	3	84	2	24	3	108
Federal Lunch Status						
Free	68	1,735	37	379	73	2,114
Reduced	10	247	4	38	10	285
Full Price	9	221	25	253	17	474
Non-participants	4	94	58	596		690
Ever received WIC – 1997						
Yes	53	291	5	10	41	301
No	47	257	95	179	59	436
Missing		1,990		836		2,826
Ever Applied for Government Assistance						
Yes	30	698	3	31	22	729
No	70	1,637	97	912	78	2,549
Missing		203		82		285

* $p < .05$

Descriptive analysis of low-income individuals. After using the benchmark to sort the CDS population into low-income and high-income groups, I compiled descriptive characteristics of the two groups (Table 14). While the benchmarks identified close to 50% of individuals as low-income at each wave, overall 71% of the CDS sample was identified low-income at least once. The high identification rate was consistent with the PSID practice of oversampling low-income families (Institute for Social Research, 2013). Although there were no differences by gender ($\chi^2 = .390$, $p = .554$), descriptive statistics suggested that low-income individuals were more likely to be underrepresented minorities.

Rates of participation in government assistance programs indicated that the low-income benchmarks identified a vast majority of individuals whose families had applied for government assistance or participated in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) up to age five. The low-income group also showed a 78% participation rate in the Federal School Lunch Program. These participation rates were expected due to the low-income group's mean family income of $27,873. Conversely, the high-income lunch program participation rate of 41% was surprising, considering the group's higher mean income of $85,806.

For all measured domains, the low-income CDS group showed worse outcomes. Academically, low-income individuals had mean math percentile ranks (51st) that were 20 percentile points lower than their higher income peers (72nd), $F(1, 1{,}362) = 134.189$, $p < .001$. Low-income degree completion rates (22%) were also half those in the higher income group (52%), $F(1, 2{,}207) = 260.988$, $p < .001$. To gain further understanding of academic success in the CDS population, Research Question 3 explores the level of achievement associated with postsecondary degree completion.

Question 3

What level of academic achievement is associated with academically successful postsecondary degree completion? The first two research questions developed the benchmark for low-income status by determining the elevated level of risk exposure related to reduced odds of post-secondary degree completion and finding the mean level of family income for individuals at the level of elevated risk. The purpose of the third research question was to further investigate postsecondary degree completion and its relationship with academic achievement in mathematics or reading. The results of Question 3 informed the benchmark for selecting the sample of high achievers used for the fourth research question.

Outcome Variable

Research Question 3 used the same Postsecondary Degree Completion variable used in the Question 1 analyses. Details on this variable are listed in Table 5 and its development is discussed in Chapter 3. Postsecondary Degree Completion is a dichotomous variable with 0 indicating no degree and 1 indicating completion of at least an associate's degree. Similar to Question 1, the sample for Question 3 was limited by the 38% of CDS participants with valid scores.

Predictor Variables

The Question 3 predictor variables were Mathematics and Reading Achievement as determined by the Woodcock-Johnson Pscyho-Educational Battery (Schrank et al., 2001). Chapter 3 describes the Woodcock-Johnson tests and CDS data collection methodology in greater detail. The Question 3 analyses used scaled scores from the 2002

CDS wave, which had the highest participation rate—missing only 283 scores. The other years had fewer participants due to the number of children too young to be tested in 1997 and the number of individuals who had aged out of the CDS by 2007. In the Question 3 sample, the Mathematics Achievement variable had a mean of 100.8, a median of 98, an *SD* of 16.2, and standard scores ranging from 55 to 171. The Reading achievement variable had a mean of 101.8, a median of 99, an *SD* of 18.7, and standard scores ranging from 30 to 193. Scores for both variables were normally distributed with skewness and kurtosis values ranging from .075 to 1.966 (Lomax & Hahs-Vaughn, 2012).

Sampling

The descriptive comparison in Table 15 contrasts the individuals included in the Question 3 sample with those in the overall CDS population. Although the Question 3 sample was similar to the Question 1 sample, more individuals were excluded due to missing Mathematics and Reading Achievement scores. Chi-square analyses determined that while the excluded and included individuals did not differ by race, the Question 3 sample was more female, higher income, and higher achieving than the excluded individuals. The biased sample was most likely to influence the analysis by including greater numbers of individuals who had obtained postsecondary degrees. However, as discussed in the Question 1 section, the CDS population had lower degree completion rates than the national population (NCES, 2013d; 2013e), thus the sample bias was unlikely to skew the results unless an unlikely number of lower achieving degree completers was in the excluded group.

Table 15.

Characteristics of the Question 3 Sample Compared With the CDS Population

	CDS Population		Q3 Sample	
Criteria	%	n	%	n
Total	100	3563	30	1,076
Sex*				
Male	51	1,813	47	501
Female	49	1,750	53	575
Race/Ethnicity				
White	46	1,642	47	503
Black	41	1,455	42	453
Hispanic	8	267	7	71
Asian	2	64	1	14
Am. Indian	1	19	0	1
Other	3	108	3	31
1997 Income Quintile*				
1 < $14,676	20	713	16	177
2 < $27,800	20	715	18	198
3 < $43,220	20	710	19	206
4 < $65,000	20	716	22	233
5 > $65,000	20	709	24	262
1997 Mathematics Quintile*				
1 < 20^{th}	14	317	9	84
2 < 40th	16	348	13	118
3 < 60th	20	443	19	178
4 < 80th	19	410	19	170
5 > 80th	31	691	40	367
1997 Reading Quintile *				
1 < 20^{th}	16	240	10	94
2 < 40th	17	258	15	138
3 < 60th	18	276	19	173
4 < 80th	17	261	19	176
5 > 80th	32	485	37	334

Note. Mathematics and Reading n < 3563.
* $p < .05$

Results of Statistical Analyses

The Question 3 analysis relied on two logistic regression tests, with Mathematics and Reading Achievement predicting the odds of Degree Completion. Two separate regressions were indicated because the independent variables were both measures of academic achievement and likely to have been highly correlated.

The logistic regression equations were

$\hat{g}\,(DEGREE) = \hat{\beta}_0 + \hat{\beta}_1\text{READING}$

$\hat{g}\,(DEGREE) = \hat{\beta}_0 + \hat{\beta}_2\text{MATHEMATICS}$

The null hypothesis was that there was no relationship between Postsecondary Degree Completion and Reading or Mathematics Achievement.

$H_0 : \beta_1 = \beta_2 = 0$

Reading. I ran a logistic regression test on the Question 3 sample of 1,076 individuals to determine the relationship between Reading Achievement and Postsecondary Degree Completion. The Likelihood-ratio test indicated that the Reading model fit the data significantly better than the empty model, $\chi^2 = 92.847$, $p < .001$, but the Hosmer and Lemeshow test of goodness of fit also indicated that the model was a poor fit for the data, $\chi^2(8) = 18.960$, $p = .015$. The classification tables showed that the model correctly classified 70.0% of cases.

The reading analysis yielded the log-odds statistics of $\beta_0 = -4.526$ ($SE = .424$) and $\beta_1 = .036$ ($SE = .004$), which I used to calculate the odds of degree completion for various reading scores with the equation ODDS = $\boldsymbol{e}^{-4.526\ +\ .036(READING)}$. Table 16 reveals the resulting odds and probabilities. The odds ratio rose above the desired 1.2 threshold at the Woodcock-Johnson scaled score of 109, which is at the 73rd percentile, meaning that individuals scoring at or above the 73rd percentile in reading had higher than average probabilities of degree completion.

Table 16.

Odds and Probability of Degree Completion for Levels of Woodcock-Johnson Reading Achievement

Reading Score	Odds	Odds Ratio	Probability
60	.094	.104	8.6%
70	.135	.155	11.9%
80	.193	.239	16.2%
90	.276	.382	21.7%
100	.396	.656	28.4%
109	**.548**	**1.211**	**35.4%**
110	.568	1.314	36.2%
120	.814	4.372	44.9%
Actual CDS degree completion	.443 (408:921)	.795 (.443/.557)	30.6% (921/1329)

Note. Bold text indicates the lowest score where the odds of degree completion were greater than 1.2.

Mathematics. The mathematics logistic regression used the same sample of 1,076 CDS individuals to determine the relationship between Mathematics Achievement and Postsecondary Degree Completion. The Likelihood-ratio test indicated that the Mathematics model fit the data significantly better than the empty model, $\chi^2 = 96.496$, $p < .001$, and the Hosmer and Lemeshow test of goodness of fit also indicated that the model was a good fit for the data, $\chi^2(8) = 13.164$, $p = .106$. The model correctly classified 70.4% of cases. The better model fit and higher classification rate suggested that Mathematics Achievement provided a slightly better benchmark for academic success.

The mathematics analysis yielded the log-odds statistics of $\beta_0 = -5.141$ ($SE = .482$) and $\beta_2 = .042$ ($SE = .005$), which I used to calculate the odds of degree completion for various mathematics scores with the equation ODDS = $\boldsymbol{e}^{-5.141 + .042(MATH)}$.

Table 17 shows the resulting odds and probabilities. The odds ratio rose above the desired 1.2 threshold at the Woodcock-Johnson scaled score of 108, which is at the 70th percentile, meaning that individuals scoring at or above the 70th percentile in mathematics had higher than average odds of degree completion. *Post hoc* power analysis determined that the achieved power for both logistic regressions was an acceptable .843 (Cohen, 1992).

Table 17.

Odds and Probability of Degree Completion for Levels of Woodcock-Johnson Mathematics Achievement

Mathematics Score	Odds	Odds Ratio	Probability
60	.073	.078	6.8%
70	.111	.124	10.0%
80	.168	.203	14.4%
90	.256	.345	20.4%
100	.390	.640	28.1%
108	**.546**	**1.203**	**35.5%**
110	.594	1.463	37.3%
120	.904	9.409	47.5%
Actual CDS degree completion	.443 (408:921)	.795 (.443/.557)	30.6% (921/1329)

Note. Bold text indicates the lowest score where the odds of degree completion were greater than 1.2.

Summary of Findings: Answering the Research Question

The level of academic achievement associated with academically successful postsecondary degree completion in the CDS sample was performance at or above the 70th percentile in mathematics on the Woodcock-Johnson. The reading level associated with postsecondary degree completion was the 73rd percentile, but the model fit was slightly inferior, suggesting mathematics achievement provided the better benchmark. For comparison purposes, CDS degree completers had a mean 1997 mathematics percentile rank at the 76th percentile and non-completers ranked at the 57th percentile.

Similarly, degree completers ranked at the 74th percentile in reading, while the mean of the non-completers was at the 53rd percentile. The CDS degree completion rate of 31% further supports a benchmark that indicates 30% of the population is at higher odds of degree completion.

To identify academically successful individuals, I applied the mathematics benchmark of performance at or above the 70th percentile to the CDS population, as illustrated in Table 18. The proportion of academically successful individuals ranged from 25% to 41% of each CDS wave. A substantial number of individuals were missing scores due to their age—preschoolers in 1997 and adults in the later two waves. A larger proportion of scores was also missing from the 2002 wave because PSID determined some families no longer met criteria for inclusion in the PSID study (Institute for Social Research, 2012). About half of the PSID population met the criteria for academic success at least once.

Table 18.

Academically Successful Individuals Performing at or Above the 70th Percentile in Mathematics on the Woodcock-Johnson at Each CDS Wave

Wave	%	n	All	Missing Scores	
1997	41	905	2,209	Too young	1,036
				No score	318
2002	25	894	2,625	Aged out	154
				No score	784
2007	35	532	1,506	Aged out	1,472
				No score	102
Final	48	1556	3,214	No score	349

Efficacy of the benchmarks in identifying degree completion. The utility of the academic success benchmark depends on its ability to identify a high proportion of postsecondary degree completers. To investigate the effectiveness of the 70th percentile in mathematics benchmark, I determined the number of CDS degree completers included in the academically successful group. The academic success benchmark identified 268 of the 386 CDS degree completers, which was an identification rate of 69%. The academically successful group's degree completion rate (43%) was more than double that of the lower achievers (18%). Research Question 4 further investigates the characteristics of academically successful individuals, focusing the analysis on those from low-income families.

Question 4

Which individual, family, and school characteristics are related to low-income students' academic success? In the fourth research question, I used the benchmarks developed in the first three research questions to identify a sample of low-income, academically successful students. I then divided the sample into Resilience groups based on their ability to sustain academic success and used MANOVA, ANOVA, and discriminant analysis tests to identify the characteristics that distinguished the academically successful groups from the unsuccessful group.

Sampling

For the fourth question of the study, the sample consisted of low-income, academically successful individuals (n = 704), which was 20% of the CDS population. I identified the sample using the benchmark criteria developed in Question 2 to identify low-income individuals placed at elevated risk and the criteria from Question 3 to identify students positioned for postsecondary degree completion. Low-income individuals had family incomes at or below the income benchmarks at any wave: 1997 =

$42,126, 2002 = $47,218, and 2007 = $54,420. Academically successful individuals scored at or above the 70th percentile in mathematics on the Woodcock-Johnson.

Table 19.

Characteristics of the Question 4 Sample

Area	All CDS		Q4 Sample	
Total	3563		704	
Sex	%	n	%	n
Male	51	1813	49	346
Female	49	1750	51	358
Race/Ethnicity				
White	46	1642	50	350
Black	41	1455	37	262
Hispanic	8	267	9	62
Asian	2	64	1	7
Am. Indian	1	19	0	2
Other	3	108	3	18
1997 Income Quintile				
1 < $14,676	20	713	21	147
2 < $27,800	20	715	26	183
3 < $43,220	20	710	34	237
4 < $65,000	20	716	12	85
5 > $65,000	20	709	7	52
1997 Mathematics Quintile				
1 < 20th	14	317	4	19
2 < 40th	16	348	6	28
3 < 60th	20	443	11	56
4 < 80th	19	410	25	127
5 > 80th	31	691	54	270
Risk Score				
0	14	469	12	85
1	29	992	29	205
2	30	1013	29	202
3	18	610	17	121
4	7	252	10	72
5+	3	81	2	18
Degree Attainment				
Degree	69	947	69	175
No Degree	31	417	31	80

Due to the selection criteria, data were intentionally not missing at random for income and academic achievement. However, for descriptive purposes, Table 19 shows that the Question 4 sample included proportionally more White and fewer Black individuals than the CDS population. The Question 4 sample also included fewer individuals from the highest two income quintiles and had disproportionate representation from higher math performers. Risk scores were similarly distributed in both groups, with a slightly smaller proportion of Question 4 individuals having a risk score of 0 and a slightly larger proportion with an elevated score of 4. Despite the higher achievement levels of the Question 4 sample, degree attainment was identical to the CDS population.

Grouping Variables

Resilience groups. I placed the CDS population into three groups based on their individual ability to maintain academic success across two consecutive CDS waves, as determined by Woodcock Johnson Mathematics scores at or above the 70th percentile. Persistent-Resilient individuals maintained academic success across two or more CDS waves. Improved-Resilient students were initially lower achievers who achieved academic success at their final wave. Non-Resilient individuals had at one time demonstrated academic success, but declined in achievement by their final CDS wave. Lower Achieving individuals did not demonstrate scores at or above the 70th percentile at any wave. It is important to note that, by definition, the three group labels including the word *resilient* are only appropriate when applied to the low-income individuals placed at statistical risk or to individuals directly exposed to significant adversity (Luthar, 1993; Masten, 2001).

The data were sufficient to place 2,338 of the 3,563 CDS individuals into resilience groups, as shown in Table 20. Data were missing from one-third of the CDS population because 154 individuals aged out of the CDS before the 2002 wave and 1,071 lacked two consecutive mathematics scores. An examination of the distribution patterns shows that Lower Achieving individuals comprised the largest group, followed by Persistent-Resilient and Non-Resilient individuals, and the smallest group of Improved-Resilient individuals. The final proportion of Non-Resilient students was higher than their representation in the individual waves due to 107 Interval I Persistent or Improved individuals who declined in performance during Interval II. At both intervals, individuals were more likely to decline in performance than to improve, suggesting that the difference was not solely due to the anticipated movement of marginal cases across the benchmark.

Table 20.

Resilience Status at Intervals I and II With Final Resilience Classification and Comparison by Income Status

Group	Persistent-Resilient		Improved-Resilient		Non-Resilient		Lower Achieving		All
	%	n	%	n	%	n	%	n	
Interval I: 97-02	24	420	9	162	18	309	48	826	1717
Interval II: 02-07	25	330	11	141	13	173	52	684	1328
Final Status	23	529	10	242	20	469	47	1098	2338
Low-Income	15	242	10	158	19	304	57	938	1642
High-Income	41	287	12	84	24	165	23	160	696

Note. The shaded cells indicate the Question 4 sample.

School Level. School Level served as a covariate to determine whether the dependent variables were affected by the varying ages of the participants. Table 21 shows the cross-tabulated distribution of the Question 4 Resilience Status and School Level groups. I coded individuals who were in Grades 6, 7, or 8 in 2002 or 2007 as Middle School and students who were in Grades 9, 10, 11, or 12 in 2002 or 2007 as High School. For the 3065 individuals from the listed grades during the 1997 and 2002 waves, 319 students could have been coded as both Middle and High School, due to their inclusion at both intervals. Because Resilience group designation was based on individuals' performance at their final wave, I chose to code dual interval students as High School. The final school level counts for the entire CDS population were 1,136 Middle School and 1,929 High School individuals. The Question 4 sample included only the 278 Middle School and 385 High School individuals who were identified both academically successful and low-income. Chi-square analyses determined that the school level groups were not significantly different by race (p = .266) or sex (p = .161).

Table 21.

Factorial MANOVA Groups: Resilience Status By Grade Span in the Question 4 Sample

	Resilience Status		
Grade Spans	Persistent-Resilient	Improved-Resilient	Non-Resilient
Middle School 1 – 6 2 – 7 3 – 8	n = 116	n = 65	n = 97
High School 4 – 9 5 – 10 6 – 11 7 – 12	n = 115	n = 71	n = 199

Outcome Variables

The outcome variables for the fourth research question were the 11 Individual, Family, and School Characteristics shown in Table 22. Chapter 3 describes the construction of each variable in detail. The Individual and Family variables had little missing data in the Question 4 sample, with the exception of Family Reading, which was missing 20% of the scores. Conversely, the School variables lacked a greater proportion of scores, with 51% missing from School Safety, due to low response rates from teachers.

Table 22.

Distribution and Descriptive Statistics for Individual, Family, and School Characteristic Variables in the Question 4 Sample

Characteristics	Present		Mean	Range	*SD*
Individual	%	n			
Math Self-Efficacy	100	704	5.19	1.6 – 7.0	0.897
Positive Behaviors	100	704	4.26	2.1 – 5.0	0.506
Read Self-Efficacy	100	704	5.35	2.0 – 7.0	0.929
Self-Esteem	98	689	4.08	1.0 – 5.0	0.607
Family					
Family Reading	80	563	13.09	4.0 – 17.0	2.560
Parent Expectations	100	704	5.27	1.0 – 8.0	1.825
Parental Warmth	100	704	4.54	1.7 – 5.0	0.559
School					
Extracurricular	77	545	7.96	0.0 – 22.0	4.594
School Connected	83	585	17.59	5.0 – 30.0	6.159
School Safety	49	344	9.66	6.0 – 19.0	1.854
Supportive Friends	99	700	10.98	1.0 – 22.0	4.881

To check whether data were missing at random, I conducted chi-square analyses by sex, race, 1997 income quintile, 1997 mathematics quintile, and risk exposure scores on the four variables missing more than 10% of their scores from the Question 4 sample. I found no significant differences for included and excluded individuals for School Connectedness. Conversely, I detected income differences for Family Reading (p =.030), Extracurricular Activities (p = .028), and School Safety (p = .042), but the missing scores had no obvious pattern, with larger proportions missing at both the highest and lowest income quintiles. I also found differences in mathematics performance for Family Reading (p < .001) and Extracurricular Activities (p = .003), with a greater proportion of scores missing from lower achieving individuals. The reduced amount of lower performing mathematics students was most likely to affect the analysis of the Improved group, who were the early low performers.

Table 23.

Comparison of Resilience Groups by Race/Ethnicity and Income Status

	Persistent-Resilient	Improved-Resilient	Non-Resilient	Lower Achieving	All	
Area	%	%	%	%	%	n
Low Income (Low)	15	10	19	56	70	1642
High Income (High)	41	12	24	23	30	696
White						
Low	29	15	19	38	51	560
High	47	14	22	17	49	536
Black						
Low	6	5	20	70	89	854
High	11	6	34	50	11	110
Hispanic						
Low	11	15	13	61	91	160
High	13	13	44	31	9	16
Asian/Pacific Islander						
Low	33	7	7	53	44	15
High	84	11	5	0	56	19
American Indian						
Low	17	0	17	67	100	6
Other						
Low	16	18	7	60	82	63
High	43	0	0	57	18	14

Note. The shaded cells indicate the Question 4 sample.

Results of Statistical Analyses

Descriptive analysis. After obtaining the sample, I began by comparing simple descriptive statistics by resilience status. The demographic comparison of the resilience groups within the low-income sample found no differences between resilience groups by sex, $\chi^2(3) = .56$, $p = .905$. In fact, the male and female distributions differed by no more than one percentage point from the overall distribution pattern. By contrast, Table 23 presents an analysis by race and ethnicity that indicates the presence of substantial differences between groups.

Compared with their higher income peers, all racial and ethnic groups from the low-income sample were less likely to be persistently successful and were more likely to be persistently lower achieving. The gaps in persistent high achievement between the low- and high-income samples were particularly large for the White, Other, and Asian groups, with the differences ranging from 22 to 51 percentage points. The Asian/Pacific Islander group was most polarized by income, but the small group size ($n = 34$) precluded drawing definitive conclusions from this analysis.

Within the low-income sample, underrepresented minorities were disproportionally included in the persistently lower achieving category. The White group had the highest proportion of individuals in the two academically successful categories (44%), followed by the Asian (40%), Other (34%), Hispanic (26%), American Indian (17%), and Black (11%) groups. The substantial differences in representation for the various racial and ethnic groups in the Improved and Non-Resilient categories are further evidence to support the assertion that they include more than marginal scores moving across the benchmark. Notably, Hispanic and Other individuals had disproportionally high representation in the Improved group and lower representation in the Non-Resilient group.

Table 24.

Comparison of Resilience Groups by Academic Rank, Degree Completion, Risk Exposure, and Income Level

	Persistent-Resilient	Improved-Resilient	Non-Resilient	Lower Achieving	All
1997 Income					
Low***	35,028[a]	29,768[b]	29,952[b]	25,325[c]	28,039
High***	95,763[a]	77,705[b]	80,449[ab]	72,997[b]	84,720
Risk Exposure					
Low**	1.8[a]	2.0[ab]	2.0[ab]	2.2[b]	2.1
High**	1.2[a]	1.4[ab]	1.2[ab]	1.6[b]	1.3
Modified Risk					
Low***	1.9[a]	2.1[ab]	2.2[bc]	2.5[c]	2.3
High***	1.3[a]	1.5[a]	1.5[a]	2.0[b]	1.5
97 Reading Rank					
Low***	83[a]	65[b]	65[b]	39[c]	52
High***	82[a]	64[b]	73[b]	47[c]	71
07 Reading Rank					
Low***	75[a]	61[b]	42[c]	29[d]	43
High***	76[a]	70[a]	57[b]	44[c]	63
97 Mathematics Rank					
Low***	89[a]	48[b]	76[c]	34[d]	51
High***	92[a]	53[b]	81[c]	43[d]	74
07 Mathematics Rank					
Low***	89[a]	84[b]	46[c]	32[d]	50
High***	89[a]	86[a]	50[b]	39[c]	68
Degree Completion					
Low***	.48[a]	.45[a]	.18[b]	.15[b]	.22
High***	.64[a]	.44[ab]	.40[b]	.33[b]	.49

Note. The shaded cells indicate inclusion in the Question 4 sample. Within each characteristic, groups with the same superscript were not significantly different from one another.
** $p < .01$. *** $p < .001$

Table 24 summarizes background differences among students classified into the four resilience groups. All positive characteristics were in the direction of high-income groups scoring above low-income groups and all negative characteristics differed in the opposite direction. Within the low-income sample, ANOVA tests found significant differences between resilience groups in family income and risk exposure. In the area of income, the Persistent group's mean was highest, the Lower Achieving group's was lowest, and the similar Improved and Non-Resilient income means fell between them with differences of about $5000 separating the three levels. Risk scores showed smaller distinctions between resilience groups. However, only the Persistent group had risk scores below the Level 2 benchmark for elevated risk.

An examination of the low-income resilience groups' mathematics and reading mean percentile ranks determined that the Persistent group ranked consistently well above average in both mathematics and reading. Conversely, the persistently lower achieving group ranked consistently well below average in both domains. Both the Improved and Non-Resilient groups' mean percentile ranks were never quite as high as the Persistent group, nor were they ever as low as the Lower Achieving group. Although the Improved group means started above average in reading and slightly below average in mathematics, ten years later the group mean had changed little in reading, but increased by 36 percentile points to well-above average in mathematics. Conversely, the Non-Resilient group means started out above average in Reading and well-above average in mathematics, but fell 23 percentile points in reading and 30 points in mathematics to slightly below average in both by 2007. While interpreting the means, it is important to note that sample membership changed over the 10-year period due to aging of the cohort.

Degree completion rates also showed significant differences between both the high- and low-income samples and between resilience groups. Within the low-income sample the two academically successful groups differed significantly from the two academically unsuccessful groups. Although the successful groups had degree completion rates 50% higher than the overall CDS completion rate of 31%, the unsuccessful groups' rates were 50% lower. By contrast, all four of the high-income resilience groups had degree completion rates above the overall CDS population's rate, with the 64% Persistent rate more than double that of the overall group's.

MANOVAs. The research design included three separate 2 x 3 MANOVAs to determine significant Individual, Family, and School characteristics related to resilience group membership. The covariates were the 2-level grade spans and the 3-level resilience status. The null hypothesis was that no differences existed between resilience groups on any Individual, Family, or School variables by school level.

$$H_0: \mu_{1\cdot v} = \mu_{2\cdot v} = \mu_{3\cdot v}$$

$$H_0: \frac{\mu_{11v}+\mu_{12v}}{2} = \frac{\mu_{21v}+\mu_{22v}}{2} = \frac{\mu_{31v}+\mu_{32v}}{2}$$

Individual Characteristics. The four dependent variables Math Self-Efficacy, Positive Behaviors, Reading Self-Efficacy, and Self-Esteem met the assumptions of univariate and multivariate normality, but not the assumption homogeneity of variance, Box's Test M= 81.689, $F(50, 360{,}544) = 1.604$, $p = .004$. Omnibus MANOVA results indicated non-significant differences in groups by Resilience category, Pillai's Trace = .022, $F(8, 1280) = 1.767$, $p = .079$ ($\alpha = .05$, two-tailed). The MANOVA test also found no significant interaction effects between Resilience groups by School Level, Pillai's Trace = .015, $F(8, 1280) = 1.675$, $p = .100$.

Although the p-value from the Resilience MANOVA test failed to reach the level of significance, I ran individual ANOVA tests because there were disproportionate missing data for the three variables. The individual ANOVA tests identified significant differences between Resilience groups in Mathematics Self-Efficacy and Self-Esteem, as shown in Table 25. Follow-up Games-Howell *post hoc* comparisons determined that the Improved group had higher self-efficacy in mathematics (p = .047) and higher self-esteem (p = .016) than the Non-resilient group. However, in addition to their questionable significance values, the effect sizes for both Self-Esteem (d = .27) and Math Self-efficacy (d = .14) were small (Cohen, 1992), indicating that they were not necessarily important features in distinguishing between resilience groups.

Table 25.

Results of ANOVA and Follow-Up Tests for Individual Characteristics

	ANOVA			Contrasts		
Variable	*df*	*F*	*p*	Persistent	Improved	Non-Resilient
Self-Esteem	(2, 686)	3.852	.022	4.10[ab]	4.17[a]	4.01[b]
Math Self-Efficacy	(2, 701)	3.044	.048	5.23[ab]	5.31[a]	5.10[b]
Positive Behaviors	(2, 701)	.439	.645	4.28[a]	4.24[a]	4.25[a]
Read Self-Efficacy	(2, 701)	.080	.923	5.37[a]	5.34[a]	5.35[a]

Note. Within each characteristic, groups with the same superscript were not significantly different from one another.

Family Characteristics. The dependent variables Family Reading and Parental Expectations met the assumptions of univariate and multivariate normality and the assumption homogeneity of variance. Parental Warmth showed a slight departure from univariate normality. Omnibus MANOVA results indicated significant differences in groups by Resilience category, Pillai's Trace = .067, $F(6, 1036) = 5.974$, $p < .001$. The MANOVA test also found no significant interaction effects between Resilience groups by School level, Pillai's Trace = .008, $F(6, 1036) = .674$, $p = .671$.

As shown in Table 26, ANOVA tests identified that significant differences existed between Resilience groups for all three dependent variables. Follow-up Games-Howell *post hoc* comparisons determined that parent expectations for education were higher in the Persistent group than in both the Improved (p = .005) and the Non-Resilient (p < .001) groups. The Improved group also had parents who exhibited more warmth than the Non-Resilient group (p = .002). The Non-Resilient group was further distinguished from the other groups by lower levels of family reading than both the Persistent (p < .001) and Improved (p = .009) groups. The effect sizes for Parental Warmth (d = .34), Family Reading (d = .41) and Expected Education (d = .45), were small to medium (Cohen, 1992).

Table 26.

Results of ANOVA and Follow-Up Tests for Family Characteristics

	ANOVA			Contrasts		
Variable	*df*	*F*	*p*	Persistent	Improved	Non-Resilient
Parent Expectations	(2, 701)	13.202	< .001	5.74^{a}	5.15^{b}	4.96^{b}
Family Reading	(2, 560)	9.474	< .001	13.57^{a}	13.37^{a}	12.56^{b}
Parental Warmth	(2, 701)	6.348	.002	4.56^{ab}	4.65^{a}	4.46^{b}

Note. Within each characteristic, groups with the same superscript were not significantly different from one another.

School Characteristics. The four dependent variables Extracurricular Activities, School Connectedness, School Safety, and Supportive Friends met the assumptions of univariate and multivariate normality and the assumption homogeneity of variance. Omnibus MANOVA results indicated significant differences in groups by Resilience category, Pillai's Trace = .069, F(8, 442) = 1.974, p = .048. The MANOVA test found no significant interaction effects between Resilience groups by School level, Pillai's Trace = .039, $F(8, 442) = 1.085$, $p = .373$.

ANOVA tests determined that significant differences existed between Resilience groups for only Extracurricular Activities, as shown in Table 27. Follow-up Games-Howell *post hoc* comparisons determined that the Persistent group had higher extracurricular participation than the Improved ($p = .012$) and Non-Resilient ($p < .001$) groups. The effect size for Extracurricular Activities ($d = .45$) was medium (Cohen, 1992). *Post hoc* power analysis found the achieved powers for all MANOVA and ANOVA tests were an acceptable 1.0 (Cohen, 1992).

Table 27.

Results of ANOVA and Follow-Up Tests for School Characteristics

	ANOVA			Contrasts		
Variable	*df*	*F*	*p*	Persistent	Improved	Non-Resilient
Extracurricular	(2, 542)	10.827	< .001	9.11^a	7.65^b	7.07^b
Supportive Friends	(2, 697)	1.588	.205	11.00^a	10.41^a	11.26^a
School Connected	(2, 582)	1.152	.317	18.11^a	17.32^a	17.29^a
School Safety	(2, 341)	.956	.385	9.51^a	9.62^a	9.82^a

Note. Within each characteristic, groups with the same superscript were not significantly different from one another.

Discriminant analysis. I conducted discriminant analysis to determine the combination of variables that best distinguished between resilience groups. The analysis used the Modified Risk Exposure scores and the significant variables from the ANOVA analyses: Extracurricular Activities, Family Reading, Math Self-Efficacy, Parent Expectations, Parental Warmth, and Self-Esteem. Function 1, named the Resilience Function, was significant, Wilks $\lambda = .904$, $\chi^2(14) = 48.056$, $p < .001$. With an Eigenvalue of .082, the Resilience Model explained 77.8% of the variance between Resilience Groups.

Analyses of the function correlations and standardized coefficients, as shown in Table 28, indicated that Family Reading, Extracurricular Activities, Parent Expectations, and Math Self-efficacy had correlation coefficients and standardized coefficients above the .3 threshold, indicating that they contributed most to the Resilience Function, with Family Reading designated the most important variable. The lower values for the other variables suggested they contributed little to distinguishing between resilience groups in the model. Although Self-Esteem's correlation coefficient was above the .3 threshold, the lower standardized coefficient indicated that it was redundant to the function.

Table 28.

Discriminant Analysis Results for the Resilience Function

Variable	Correlation	Standardized Coefficient
Family Reading	.610	.539
Extracurricular Activities	.510	.359
Parent Expectations	.480	.357
Math Self-Efficacy	.360	.376
Self-Esteem	.401	.262
Parental Warmth	.285	.084
Modified Risk Exposure	-.258	-.204

Note. Variables above the line contributed significantly to the function.

An ANOVA test on the discriminant scores determined that the Resilience Function significantly discriminated between groups. $F(2, 477) = 19.445$, $p < .001$. Follow up Games-Howell tests showed that the function discriminated the Non-Resilient group from the Persistent and Improved ($p < .001$) groups, but did not discriminate between the Persistent and Improved groups. Specifically, the Non-Resilient group was lower than the two academically successful groups in family reading, parental expectations for education, extracurricular participation, and self-efficacy in mathematics. The sample size in this analysis (*n* = 704) easily exceeded the necessary 20 individuals per variable required to achieve adequate statistical power (Stevens, 2009).

Table 29.
Discriminant Analysis Results for the Four-Group Function

Variable	Correlation	Standardized Coefficients
Math Self-Efficacy	.565	.629
Family Reading	.438	.357
Parent Expectations	.438	.415
School Safety	-.338	-.367
Extracurricular	.319	.148
School Connectedness	.265	.178
Self-Esteem	.264	.133
Positive Behaviors	.219	.088
Parental Warmth	.209	-.078
Modified Risk Exposure	-.197	-.096
Supportive Friends	-.135	-.233
Reading Self-Efficacy	.114	-.006

Note. Variables above the line contribute significantly to the function

Alternate discriminant analysis. Although the 11 tested characteristics were previously identified in the literature as significant factors related to academic success or resilience in low-income students, only six of the variables reached significance in the CDS sample. One explanation for the discrepancy may be the current study's definition of Non-Resilience as students who had at some point demonstrated high academic achievement followed by a decline in performance. Other studies' definitions of non-resilience encompassed the current study's persistently lower achievers, who were excluded from the current analysis (e.g., Borman & Overman, 2004; Finn & Rock, 1997).

To investigate whether adding the persistently lower achievers to the analysis would yield different results, I ran a second exploratory discriminant analysis. The second analysis included the entire low-income sample with all four resilience groups (Persistent, Improved, Non-Resilient, Lower-Achieving) and the 11 Individual, Family, and School Characteristics along with the Modified Risk Exposure scores. The results found one significant function, Wilks $\lambda = .780$, $\chi^2(36) = 97.408$, $p < .001$. The Eigenvalue (.218) indicated that the Four-Group function accounted for 80.6% of the variance between groups. In the Four-Group function, as shown in Table 30, self-efficacy in mathematics increased in importance and School Safety increased to significance in distinguishing between groups. Extracurricular activities moved to a lesser role, despite its correlation coefficient above .3, because the low standardized coefficient denoted redundancy.

An ANOVA test on the discriminant scores showed that the Four Group function significantly discriminated between groups $F(3, 397) = 28.788$, $p < .001$. Follow-up Games-Howell tests determined that the function discriminated the Lower Achieving group from the other three groups ($p < .001$) and distinguished the Non-Resilient group from the Persistent ($p = .007$) and Improved ($p = .035$) groups. The model did not distinguish between the Persistent and Improved groups ($p = .992$). These exploratory results indicate that in a model that included persistently lower achieving individuals, the characteristics that differentiated academically successful from unsuccessful students were higher math self-efficacy, families who read more, parents with higher educational expectations, and safer school environments.

Summary of Findings: Answering Question 4

The Question 4 analyses found a number of characteristics associated with low-income students' academic success, which was defined as mathematics performance at the level associated with increased odds of postsecondary degree completion (≥ 70th percentile). The three most significant and important variables that distinguished academically successful from non-resilient individuals were Extracurricular Activities, Parent Expectations, and Family Reading. The findings were consistent across school levels. Although persistent academic success was less common for low-income individuals and those with underrepresented minority status, I found no gender differences in resilience group membership.

Resilience group differences. The persistently high achieving group was distinct from the other achievement groups in many ways. Persistently successful individuals came from families with more resources and had significantly higher math and reading achievement levels than the other two low-income resilience groups. Although mean risk exposure levels for the persistently high achieving group were not significantly different from the other group means, they were the only low-income group with a mean below the elevated risk exposure benchmark. Persistently successful individuals had higher rates of extracurricular participation and their parents had higher educational expectations than the other resilience groups. They were also disproportionally likely to be White or Asian.

Academically improved individuals shared two characteristics with the persistently high achieving group that distinguished them from the Non-Resilient group—higher degree completion rates and increased amounts of family reading. Improved individuals were further distinguished from the Non-Resilient group by their higher overall self-esteem, greater self-efficacy in mathematics, and higher levels of parental warmth. The Improved group shared similar levels of elevated risk exposure with non-resilient and persistently lower achieving individuals. Demographically, the Improved group was disproportionally White, Hispanic, or Other.

The Non-Resilient group had an achievement trajectory opposite the Improved group's, with their mean academic ranks showing antipodal 20 percentile point changes in reading and 30 point changes in mathematics. The Non-Resilient group was distinguished from the higher achieving groups by lower levels of all of the significant variables. Although the Non-Resilient group had higher incomes and higher achievement levels than the persistently Lower Achieving group, both academically unsuccessful groups had similarly low degree completion rates. Non-Resilient individuals were disproportionally likely to be White, Black, and American Indian. Lower Achieving individuals were most likely to fall into the four underrepresented minority groups—Black, Hispanic, American Indian, and Other.

Important characteristics. The ANOVA tests identified six significant characteristics that distinguished academically successful individuals who persisted in high achievement or improved substantially to become high achievers. Of those six characteristics, three had medium effect sizes—Extracurricular Activities ($d = .45$), Parent Expectations ($d = .45$), and Family Reading ($d = .41$). The remaining three effect sizes were small—Parental Warmth ($d = .34$), Self-Esteem ($d = .27$) and Mathematics Self-Efficacy ($d = .14$). The primacy of the three most important characteristics was reinforced by the results of the discriminant analysis, which also elevated math self-efficacy into importance in distinguishing between academically successful and non-resilient groups. Furthermore, correlations of the 11 characteristics with actual degree completion scores for individuals in the Question 4 sample showed that Parent Expectations (r_{pb} = .26) and Extracurricular Activities (r_{pb} = .26) were the only significant variables with non-trivial effect sizes. The following paragraphs further explore the meaning of the group differences for the significant variables in their order of relative importance.

For the Parent Expectations variable, the Non-Resilient (*M* = 4.96, *SD* = 1.9) and Improved (*M* = 5.15, *SD* = 1.9) means reflected an average parental expectation of a 2-year college degree, while the Persistent (*M* = 5.74, *SD* = 1.6) mean was equivalent to the average parental expectation of a 4-year degree. A clear majority (70%) of all low-income parents expected that their children would receive either a 2- or 4-year degree. The bachelor's degree expectation rates for the three resilience groups were similar, at just above 50%. By contrast, 23% of Improved and 24% Non-Resilient parents only expected their children to graduate from high school, compared with 10% of Persistent parents. Conversely, 24% of Persistent parents expected their children to achieve master's or doctorate degrees, compared with 16% of Improved parents and 9% of Non-Resilient parents.

Extracurricular Activities scores represented the frequency of playing a musical instrument, school sports, school clubs, scouts or hobby clubs, and volunteer service activities on a scale from 1 (less than once a month) to 6 (every day). While mean Persistent scores (*M* = 9.11, *SD* = 4.6) were significantly different than Improved (*M* =

7.65, *SD* = 4.5) and Non-Resilient (*M* = 7.07, *SD* = 4.4) scores, aggregation obscured whether the differences were due to participation in a greater variety of activities or if they were due to increased intensity of involvement. A disaggregated analysis determined that the Persistent group was involved in an average of 2.4 activities with 38% of them at the intensity of multiple times a week or every day—the equivalent of one high intensity activity and one or two low intensity activities. The Improved and Non-Resilient groups averaged 2.0 activities, with intensity levels of 46% and 45%—the equivalent of one high and one low intensity activity. Non-Resilient individuals were also twice as likely to be involved in no extracurricular activities (9%, n = 27) than those who were Persistent (5%, n = 11) or Improved (4%, n = 7).

Interpreting the Family Reading variable proved to be more challenging. The Family Reading means were based on the sums of responses to three questions with scores reflecting reading frequency on a 1 to 6 scale and number of books in the home on a 1 to 5 scale. The maximum potential score was 17 points, and the means for the resilience groups were 13.57 for Persistent (*SD* = 2.5), 13.37 for Improved (*SD* = 2.7), and 12.56 for Non-Resilient (*SD* = 2.5). The difference between the Persistent and Non-Resilient groups was the equivalent of a one-level reduction in reading frequency for parent or child (e.g. a few times a week instead of every day), or one level decrease in books in the home (e.g. 10 to 20 instead of 20 or more).

The self-esteem scores reflected the mean of child responses to nine questions related to how well they do things, how others perceive them, and whether they like themselves on a scale from 1 to 5. The lack of effect size was most likely due to consistently high self-esteem among the three groups, ranging from 4.01 for the Non-

Resilient group to 4.17 for the Improved group. The higher *SD* of .63 for the Non-Resilient group (compared with .56 for Improved and .59 for Persistent) indicates slightly greater variability in scores than for the other two groups.

The smaller effect size was unsurprising for Parental Warmth, due to the variable's departure from normality. Scores reflected a summed count of six dichotomous items related to parental interactions with their children. The score distribution skewed high, reflecting that warm parental interactions were commonly reported among the sample. The means of the resilience groups ranged from 4.46 for the Non-Resilient group to 4.65 for the Improved group, suggesting that for each group it was typical for between four and five of the six dichotomous items to indicate the presence of warm parenting behaviors. The higher SD of .60 for the Non-Resilient group (compared with .52 for both Improved and Persistent) indicates slightly greater variability in scores than for the other two groups.

Mathematics Self-Efficacy scores were based a series of 10 questions regarding how important individuals perceived mathematics to be, interest in and enjoyment of mathematics, and self-assessment of skill levels relative to peers on a 1 to 7 scale. The Mathematics Self-Efficacy scores reflected the mean of the 10 items, with a maximum score of 7. The two significantly different means—Improved (M = 5.31) and Non-Resilient (M = 5.10)—varied by the equivalent of two questions that were answered one point lower on the scale, or one question that was answered two points lower on the scale. The higher SD of .94 for the Non-Resilient group (compared with .85 for Improved and .86 for Persistent) indicates slightly greater variability in scores than for the other two groups.

Summary. The tests of statistical significance only indicated the likelihood that group differences were due to chance instead of sampling variability (Kirk, 1996). Therefore, determining whether those differences were relevant or practically important required further analysis. After examining the effect sizes for the current study's six significant variables and analyzing the differences in terms of the interview responses, I concluded that only a few of the significant characteristics reached the level of practical importance in terms of observable behaviors. The differences for parental warmth, self-esteem, and mathematics self-efficacy were trivial in terms of practical application. Additionally, the implications of the family reading differences were less clear and require a more in-depth analysis than was possible in the current study. However, both parent educational expectations and extracurricular activities showed practical differences between groups, such as fewer students uninvolved in extracurricular activities and more parents who predicted their children would obtain graduate degrees.

Chapter 5

Discussion and Implications

The current study sought to investigate the relationships between various characteristics of disadvantaged students and the level of K – 12 academic success that positioned them for postsecondary degree completion. To that end, a series of statistical tests using samples from a national pool of 3,563 individuals yielded a number of important findings. This chapter lists the notable findings, highlights the study's strengths and limitations, interprets the implications of the findings and methodology in relation to prior research results, and provides recommendations for future practice and research.

Notable Findings

During the process of exploring the four research questions, the current study uncovered four major findings. First, at a relatively low level of two direct risks an individual's odds of postsecondary degree completion became unlikely. Second, the income level associated with elevated risk levels encompassed roughly the lower half of the CDS population. Third, individuals with mathematics achievement at or above the 70th percentile on the Woodcock-Johnson were more likely to obtain postsecondary degrees. Fourth, the most significant and important characteristics associated with persistent academic success for low-income students, across school levels, were increased participation in extracurricular activities and high parental expectations for education.

Strengths and Limitations of the Study

The use of the PSID, CDS, and TAS data sets was one of the current study's major strengths. This large, nationally representative sample offered a strong and reliable source of data related to the risks and outcomes associated with poverty (McGonagle et al., 2012). Its extensive information related to psychosocial wellness, health, and academic achievement allowed the current study to conduct a comprehensive analysis of risk, academic achievement, and degree completion. The uniqueness of the data source was also important because a number of educational studies relevant to the current topic used the NELS:88 data set (e.g., Broh, 2002; Finn & Rock, 1997; Lipscomb, 2006; Snellman, Silva, Frederick, & Putnam, 2015; Wyner et al., 2007; Yan & Lin, 2005) and the current study's replication of prior findings with a different sample strengthens those particular claims. Despite its many strengths, the PSID oversampled low-income and Black individuals and suffered from disproportionate missing data from poorer, lower achieving, higher risk individuals, which should be considered when generalizing the current study's results to a wider population.

A second strength of the current study was the research design's calculated efforts to accurately identify low-income, academically successful students. In this regard the current study departed from previous methodology that used arbitrary cut-off points, instead developing low-income status and academic success benchmarks with statistical relationships to proximal risk and degree completion. Consequently, both benchmarks directly or indirectly derived their validity from the degree completion data, which was limited by missing scores for approximately two-thirds of the CDS population. Fortunately, the TAS study is ongoing and will provide opportunities to revisit and enhance the degree completion data in the future.

Table 30.

Comparison of Current Study with Similar Studies by Methodology and Effect Size

Criteria	Current Study	Borman & Overman, 2004	Finn & Rock, 1997
Sample	CDS All races & ethnicities Grades K-12	Prospects Black, Hispanic, & White Grades 3-6	NELS:88 Black & Hispanic Grades 8 -12
Academic Success	Math test scores ≥ 70^{th} percentile	Math test score median = 59th percentile	Math and reading test scores ≥ 40th percentile
Low Income	Approximately lowest half of income distribution	Lowest third of SES composite measure	Lower half of SES composite measure
Math Self-Efficacy	.14	.27	-
Positive Behaviors	NS	-	.82
Read Self-Efficacy	NS	-	-
Self-Esteem	.27	.21	-
Family Reading	.41	-	-
Parent Expectations	.45	-	-
Parental Warmth	.34	-	-
Extracurricular	.45	-	NS
School Connected	NS	.75	-
School Safety	NS	.19	-
Supportive Friends	NS	-	-

Note. Significant findings are indicated by their effect sizes (current study and Borman & Overman = Cohen's *d,* Finn & Rock = Mahalanobis distance*)*. NS = non-significant

The findings of the current study departed from prior findings in several areas, as shown in Table 30, possibly due to operational definitions or methodological differences. The research design attempted to control for factors unrelated to academic resilience (e.g., learning disabilities and low cognitive ability) by limiting the analysis to students who demonstrated achievement above the academic benchmark. This methodology yielded a definition of non-resilience that excluded persistently lower achievers, in contrast to other studies that included them in their non-resilient group (e.g., Borman & Overman, 2004; Finn & Rock, 1997). The results of the current study's exploratory discriminant analysis suggested that if the current study had included persistently lower achievers it may have yielded results for school safety, math self-efficacy, and extracurricular participation that were more similar to the comparison studies. This is particularly relevant to the current study's contradiction of Finn and Rock (1997), who determined that extracurricular activities had no significant effects on academic achievement, perhaps due to their inclusion of persistently low achievers or due to their failure to factor in the intensity level of extracurricular involvement. The current study's primary focus on higher achievers renders its claims strongest when distinguishing between high achievers who persist and those who decline and provides little information about the differences between lower achievers who improve and those who do not.

Similarly, interpretations of the current study's findings should consider methodological differences in data sources. Although some variables (e.g., Self Esteem and Parent Expectations) closely replicated the methodology of prior studies, other variables were unique to the CDS. For example, Finn & Rock's (1997) findings on academic resilience emphasized the importance (D = .82) of positive personal qualities and behaviors *as reported by teachers*. Conversely, the current study had non-significant findings when examining the effects of similar positive behaviors *as reported by parents*. Similarly, *students* provided the non-significant school connectedness data in the current study, whereas the source of Borman and Overman's (2004) similar significant and important (d = .75) variable of school engagement was *teachers*. Consequently, it is difficult to know whether the differences in findings may be attributed to the current study's higher bar for academic success or to the varying perspectives and biases of students, teachers, and parents.

The research methodology also excluded potential risk sub-variables that lacked evidence of direct adverse exposure, departing from prior studies that mixed proximal and distal risks together (e.g. Lucio et al., 2012; Sameroff et al., 1993). This approach yielded a measure of risk exposure that was more focused—and potentially more accurate—in the current study. Although the risk variable was fairly comprehensive in scope and included nine proximal risks, it was still vulnerable to error from unaccounted risks. One potential source of unaccounted risk was use of the same risk exposure range for all individuals, despite their age. This choice represented a trade-off because it prevented older participants from having higher risk counts simply due to additional time, but it also potentially overlooked risks from the formative preschool years of the older students. An additional limitation was the five-year interval design of the CDS. The only data available consistently throughout the risk variable's ten-year period was PSID family upheaval data. The other variables may have been less complete because they were only reported once or twice during the same time frame. Finally, the risk analysis was limited to the data collected by the CDS, allowing for the possibility that an important risk sub-variable was uncounted simply due to unavailability.

Overall, the current study's research methodology provided a comprehensive analysis of academic success in relation to income, academic performance level, school level, and risk. The study additionally captured the academic trajectories of many individuals from the beginning of their school careers to degree completion. However, the statistical models did not seek to understand interaction effects, and thus may not have detected some of the underlying mechanisms related to academic resilience. The large-scale survey design also limits the conclusions that can be drawn from the study to correlational observations and does not allow for the determination of causal relationships.

Discussion

In an effort to better understand the underachievement of low-income students, the current study extended the resilience research base through a singular focus on proximal risk exposure and through an examination of resilience in relation to the positive adaptive outcome of associate's or bachelor's degree completion. The statistical analyses determined that at the relatively low exposure of two or more proximal risks CDS individuals had reduced odds of degree completion. These proximal risks included a parent exiting the household, food insecurity, housing insecurity, health problems, low cognitive stimulation, lack of emotional support from the primary caregiver, use of violence to settle family conflicts, high parental stress levels, and a parent in psychological distress. The study's determination that the benchmark for elevated risk was only two risk exposures suggests that although many children may have the internal resources and external supports to adapt to one adverse environmental condition, the addition of a second risk exposure may overwhelm their adaptive capacities.

In the CDS sample, risk exposure levels had negative associations with academic achievement, supporting the similar findings of Robinson et al. (2002) and Rouse and Fantuzzo (2009). Consequently, persistently high-achieving individuals were the only low-income resilience group with a mean risk exposure level below the elevated benchmark. The lower risk exposures and higher family incomes for persistent high achievers were congruent with Robinson et al.'s (2002) findings that the highest achieving former Head Start students had been exposed to fewer stressors and had more family resources. The lesser risk exposure levels of low-income high achievers also supported Luthar's (1993) assertion that some students labeled *resilient* due to membership in statistically high-risk groups may actually fail to meet the operational definition for resilience because they have not been exposed to directly adverse conditions.

The relatively low benchmark for elevated risk led to a relatively high benchmark for low-income status, due to the negative association between income and risk (Evans & English, 2002). The benchmark for elevated risk was slightly above the population's median income, validating the methodology of prior researchers who have labeled the lower halves of their income distributions as low-income (e.g., Finn & Rock, 1997; Wyner et al., 2007). The findings of the current study indicated that CDS individuals below the median income had not only reduced odds of degree completion, but also differences in academic achievement trajectories, racial and ethnic distributions, and proximal risk exposures when compared to their higher income peers.

The CDS income benchmarks suggested that elevated proximal risk exposures and lower odds of postsecondary degree completion extend well beyond the group of children living below the federal poverty line. According to Cashell (2008), the income distribution below the median also includes the working class and part of the lower middle class. Specifically, Cashell noted substantial overlap between social class designations, with the working class encompassing individuals earning between the federal poverty line ($20,650 for a family of four in 2007) and $52,500, and the middle class encompassing incomes between $40,000 and $100,000. By comparison, the current study's CDS low-income income benchmark was the equivalent of $54,420 in 2007 (Bureau of Labor Statistics, n.d.), placing working-class and lower-middle-class children well within the low-income group.

To some observers the low-income benchmarks may seem too high, but evidence suggests that many families well above the poverty line are experiencing economic anxiety and distress. The National Center for Children in Poverty calculated a basic needs budget based on modest assumptions of costs related to food, clothing and shelter for various geographic locations (Cauthen & Fass, 2008). They determined that a family of four would require from $43,376 in a rural area to $67,692 in urban New York just to meet their basic needs, with no emergency reserves or savings for the future. Cauthen and Fass (2008) concluded that the federal poverty line is a "measure of deprivation and extreme hardship" (p. 3) and that a large number of working- and middle-class families are not making enough money to weather a health or employment crisis, or even to meet all of their basic needs, particularly in urban areas. Given these calculations, it is less surprising that a significant proportion of CDS children below the median income were exposed to proximal risks such as housing instability, food insecurity, and parental stress.

The low proximal risk benchmark, high income benchmark, and subsequent discrepancies in findings between the current study and prior resilience studies may be attributed to the research design's shift away from defining academic success as "better than expected" performance (e.g., Borman & Overman, 2004) or an "absence of failure" (e.g., Finn & Rock, 1997). The theoretical difference between the current and aforementioned approaches to academic success represents a transfer of focus from factors associated with persistent low achievement or high school dropout to a focus on the high academic achievement associated with eventual degree completion. In the CDS sample, this high achievement benchmark was achievement in mathematics at or above the 70th percentile. The efficacy of mathematics as a better indicator than reading achievement was unsurprising due to similar findings in prior studies regarding the strong association between mathematics performance and overall academic achievement (Adelman, 2006; Sirin, 2005).

Descriptive analyses showed higher than average degree attainment rates for students performing persistently above the 70th percentile in mathematics, particularly for those from higher income families. However, the CDS degree completion rate of 43% for persistent high achievers provides evidence that achievement above the academic benchmark represents merely an increase in odds—and not a guarantee—of degree completion. Likewise, even among persistently lower achievers, 18% went on to complete postsecondary degrees, although this was a far more likely outcome for affluent individuals. It is important to explicitly state that the purpose of the academic achievement benchmark was not to create expectations for future achievement based on students' prior achievement levels, but to provide a statistical tool for signaling whether a student was on track for eventual degree completion.

Unfortunately, the CDS data showed that most low-income students were off-track for degree completion. Similar to Xiang et al. (2011) and Wyner et al. (2007), the current study determined that low-income students attained and maintained high academic achievement at lower rates than their higher income peers. In the CDS population, 15% of low-income individuals maintained high achievement while 19%

declined in performance and only 10% improved enough to enter the high-achieving group. Of particular concern, low-income high achievers who declined in performance had long-term non-resilient outcomes, with reduced degree attainment rates similar to persistent lower achievers. This is in direct contrast to the lower achieving high-income groups, who still had above average degree attainment rates. Resilience theory attributes the inability of the low-income students to recover their former achievement levels to the adaptive interactions between the individuals, their external supports, and their environmental conditions (Luthar, 2006).

The current study found that the main characteristics differentiating between the low-income students who persisted in high achievement and those who declined were external supports, rather than individual attributes. All three low-income resilience groups showed relatively high levels of self-esteem, self-efficacy, and positive behaviors. The major differentiating characteristics between persistent high achievers and academically non-resilient individuals in the CDS sample were extracurricular involvement and high parental expectations, which both had similar moderate effect sizes (d = .45) and significant correlations with degree completion.

The documented positive relationship between extracurricular involvement and academic achievement was consistent with the results of numerous prior researchers (Broh, 2002; Hébert & Reis, 1999; Lipscomb, 2006; Perez et al., 2009), despite restriction of the current analysis to low-income learners and a stringent definition of academic success related to degree completion. Other studies have also validated the importance of parental expectations for education in promoting children's academic achievement (Davis-Kean, 2005; Stage & Hossler, 1989).

A closer analysis of CDS parental expectations determined that the parents of persistently high achieving students were more likely to anticipate their children would obtain master's or doctorate degrees and less likely to believe their children would stop at high school graduation than the parents of the students who declined in achievement. Despite these differences, parental expectations were consistently high, with a vast majority (70%) of low-income CDS parents expecting their children to obtain a postsecondary degree. In fact, low-income CDS parents' expectations were much higher than the expectations of their children's teachers, who anticipated that only 45% of their low-income students would obtain postsecondary degrees.

The literature posits that parent expectations are based on both parents' perceptions of their children's abilities and the degree to which they believe higher education is desirable or attainable (Wood, Kaplan, & McLoyd, 2007; Zhan, 2006). Because the current study restricted its main analysis to high achieving individuals, the resilience group differences in parent expectations were most likely due to factors other than low student performance. Although it is possible that some low-income parents do not think higher education is a worthwhile pursuit for their children, other parents' lowered expectations for degree completion may reflect beliefs that they lack the resources to manifest higher expectations into reality.

Evidence suggests that low-income income parents do have difficulty manifesting their high educational expectations for their children. CDS degree completion data showed that only 26% of the low-income students whose parents anticipated their children would obtain a postsecondary degree actually went on to obtain one. By contrast, a higher proportion (86%) of high-income parents expected their children to obtain postsecondary degrees and they were twice as likely (53%) as low-income parents to be correct in their predictions of degree completion. Zeehandelaar and Winkler's (2013) survey of parental preferences for schooling captures the difference between low-income parents' hopes and their realities. They found that the most disadvantaged parents ranked two student goals higher than other parents: (a) "understands how important it is to go to college," and (b) finish high school with "job skills that do not require further education" (p. 5).

The relationship between degree completion and expectations for education is more complex than parents simply verbally instructing their children to go to college or obtaining financing for higher education. Adult expectations are also demonstrated through the provision of experiences that develop children's competency beliefs and stimulate their motivation to learn (Benner & Mistry, 2007; Wigfield & Eccles, 2002), in turn influencing the extent that children academically prepare for higher education. In particular, Davis-Kean (2005) found that parent educational expectations influenced academic achievement through the pathway of family reading, which was also a significant differentiator between successful and unsuccessful students in the current study. A family culture of literacy is developed through myriad informal social interactions between parents and children that are typified by parental modeling of genuine enjoyment for reading, prioritization of learning activities, and a shared identity as readers (Klauda, 2012; Strommen & Mates, 2004). Highly educated and middle class parents also express their lofty educational expectations through substantial social and financial investments in their children (Bianchi & Robinson, 1997; Hoff, Laursen, & Tardiff, 2002), engaging in an intentional strategy of cultivation to enhance their children's skills and abilities through participation in multiple organized and extracurricular activities (Lareau, 2002).

Although the current study's analyses mainly examined individual, family, and school characteristics in isolation, the discriminant analysis considered them in combination, finding that extracurricular participation, educational expectations, family reading, and self-efficacy in mathematics together differentiated between academically successful and unsuccessful low-income students. These four characteristics typify the behaviors associated with higher income parents' intentional strategy of cultivation that exposes children to mastery experiences and positive supports from adults that contribute to ongoing educational success (Butz & Usher, 2015; Usher & Pajares, 2008). Unfortunately, low-income parents often lack the social and financial resources to equal more affluent parents' substantial investments in their children's development (Bianchi & Robinson, 1997; Hoff et al., 2002).

Differential levels of parental resources are exemplified in the area of extracurricular participation. While researchers have suggested that low-income students derive substantial benefit from extracurricular participation, they have also found that low-income students have lower participation rates at the elementary (Covay & Carbonaro, 2010) and secondary levels (Feldman & Matjasko, 2007; Snellman et al., 2015) than their higher income peers. The pattern of reduced extracurricular participation for low-income students was consistent in the CDS sample, with the extracurricular participation means of low- and high-income students differing by 18% in Persistent, 20% in Improved, and 34% in Non-Resilient students.

One reason behind lower participation rates is simply lesser access for low-income students as school districts have balanced their budgets by eliminating extracurricular programs or imposing student fees. A recent study by Snellman et al. (2015) determined that in the face of budget restrictions, wealthy districts turned to private donors to maintain healthy sports programs, while lower income schools dropped programs or instituted fees that cost an average of $600 per activity. When fees were introduced, one-third of participants whose families made less than $60,000 per year stopped participating.

Recommendations for Practice, Policy, and Research

The current study's findings have practical implications for practitioners, policy-makers, and researchers. First, policies and programs to improve educational outcomes for children placed at risk for poor educational outcomes should focus on a wider income group than just individuals in extreme poverty. Similarly, despite concerns that educational reformers are presently prioritizing low achieving students (Ballou & Springer, 2008; Center on Education Policy, 2011; Reback, 2007), the results of the current study indicate that academically successful low-income students are particularly vulnerable to academic decline, and thus equally deserving of attention. Both findings suggest that educators and policy-makers may need to set aside preconceived notions of who has been placed at risk and is in need of additional supports.

Practice and Policy

The low elevated risk benchmark suggests that school improvement strategies directed at increasing degree attainment rates should specifically focus on mitigating children's risk exposure. To that end, the Community Schools Initiative offers K-12 schools an approach specifically designed to reduce risk by providing holistic programs and services that address the emotional, physical, cognitive, and social needs of students and their families. In particular, Community School programs seek to reduce risk factors by providing access to affordable health, mental health, employment assistance, and social services for families, often before children reach school age (Blank, Melaville, & Shah, 2003). The Coalition for Community Schools has documented its programs' benefits to families by decreasing parental stress, reducing student mobility, and fulfilling the basic needs of housing, food, and employment (Dryfoos, 2000).

Educators and policy-makers can increase extracurricular participation rates by removing structural barriers that impede low-income students' participation. To increase participation rates, schools need to supply a sufficient number of age-appropriate and culturally relevant activities to accommodate high numbers of students at varying skill levels. Supporting low-income students' extracurricular participation may also require assistance with fees (Holt, Kingsley, Tink, & Scherer, 2011; Mahoney et al., 2005), equipment, or transportation (Feldman & Matjasko, 2007). Policy-makers should revisit minimum academic performance requirements that exclude motivated individuals with lower grades from participating and teachers should consider actively recruiting individuals with low extracurricular participation rates (Brown & Evans, 2002).

Studies have determined that extracurricular participation supports academic success mainly through increased access to teachers, by fostering social bonds with adults who promote pro-social and pro-academic behaviors (Broh, 2002; Brown & Evans, 2002). As evidence, in his study of high school students Broh (2002) found lack of positive effects for extracurricular activities without strong faculty involvement, such as intramural athletics. For this reason, administrators should ensure that extracurricular activity leaders are pro-social, pro-academic adults adept at fostering positive bonds with students.

Although educators may have limited ability to influence the culture of academic expectations within families, they can and should intentionally cultivate an academically optimistic culture in their schools. Researchers have determined that high teacher expectations can mitigate the effects of low parent expectations for minority and low-income learners (Benner & Mistry, 2007; Wood et al., 2007). Studies have also determined that high-performing, high-poverty schools actively cultivate optimistic school-wide cultures with an academic focus, collective student and teacher efficacy, and high expectations for both students and faculty (Hoy, Tarter, & Hoy, 2006; Kannapel & Clements, 2005).

Additionally, the gap in degree completion rates between high- and low-income persistently high achievers indicates a need for educators and policy-makers to allocate resources that enable capable disadvantaged students to access higher education. These resources should include financial support, assistance in understanding higher education options, and early notification that encourages students to become academically prepared before the end of their high school careers (Goldrick-Rab, Carter, & Wagner, 2007). One key factor in college entrance for low-income students is the on-going support of their high school guidance counselors (King, 1996). Schools need to provide sufficient access to adults that can assist low-income students in navigating the college admissions process and accessing scholarships and financial aid. Alternatively, Hoxby and Turner (2013) have found success improving college application and enrollment behaviors for low-income high achievers through no-paperwork waived application fees and a semicustomized database that offered targeted cost information to parents and students. Although these recommendations focus on K-12 education, a large body of research documents the challenges and supports associated with low-income students' ability to persist in higher education to degree completion (Goldrick-Rab et al., 2007).

Research

The current study answered four questions regarding risk exposure, academic achievement, and the characteristics associated with academic success, yielding results that reinforced and contradicted the results of prior studies. Both the study's methodology and findings have implications for researchers of risk, resilience, and low-income learners. They also raised a number of additional questions for future researchers to explore.

Academic success. Researchers investigating academically successful students should define achievement at a level high enough for individuals to be positioned for economic success in adulthood, which requires more than a high school diploma. According to Carnevale et al. (2013), by the year 2020, 65% of all jobs in the U.S. economy will require postsecondary education, with 35% requiring a bachelor's degree and 30% requiring some college or an associate's degree. Consequently, researchers of postsecondary outcomes should consider adopting the methodology of the current study and include 2-year degree attainment in their analyses, rather than focusing solely on 4-year degrees. Although the findings may be unique to the CDS sample and not necessarily generalizable to a wider population, in the current study the academic benchmark for postsecondary success was achievement at or above the 70^{th} percentile in mathematics. Alternatively, researchers may choose to study postsecondary success using a more direct measure of economic prosperity in adulthood, such as annual income.

The study's use of mathematics achievement scores to sort students into resilience groups presents the opportunity for a follow-up study of how the results may have differed if the Question 4 sample selection had instead used reading achievement data. Additionally, the current study's methodology excluded persistently lower achievers from the analyses to control for factors unrelated to resilience, which did not allow for an exploration of characteristics that differentiated between lower achievers who improved differ from those who did not. This suggests potential for a follow-up comparison of improved and persistently lower achieving students whose performances were close to the academic achievement benchmark.

Risk and income. The risk and income analyses validated the research practice of setting the benchmark for low-income status at the national median, which identified 74% of high-risk individuals. Conversely, the varying participation rates in the National School Lunch Program and the questionable relationship between free and reduced lunch status and risk in the CDS sample validated Harwell and LeBeau's (2010) concerns regarding the efficacy of using free and reduced lunch as an identifier of socioeconomic status.

To gain an accurate measure of adverse risk exposure, future researchers should reconsider the practice of mixing distal and proximal risks in their risk indices, which obscures the actual amount of direct exposure to adverse conditions. Because the current study's risk index was unique and the elevated risk exposure benchmark was fairly low, replication with another data set would strengthen the findings derived from the risk methodology. The analysis of risk and degree completion also raised questions regarding underrepresented minority status as a potential proximal risk. While the findings offer too little detail to support Burchinal's (2008) assertion that exposure to racial discrimination or fear of racial discrimination act as proximal risk factors, they do suggest this as an area for further empirical investigation.

Race and ethnicity. The current study uncovered differential results in achievement trajectories by race and ethnicity, further supporting the need for additional research into the interactions between cultural factors and resilience. The findings specifically suggest the need for a more in-depth qualitative investigation into why Black individuals were more likely to drop out of the high achieving group, why Hispanic individuals were more likely to improve in performance than other underrepresented minority groups, and the reasons behind the discrepant achievement trajectories for low- and high-income Asian and Pacific Islanders.

Data set. Educational researchers should consider using the CDS data set, which was particularly useful for the current study's investigation of the effects of risk, income, and adaptive characteristics in school-aged children. Although prior studies have suggested that adaptive characteristics may differ across contexts (Hsin, 2009; Overstreet & Braun, 1999), the current study's design did not investigate interaction effects. However, the CDS data set may be suited for an investigation into interaction effects between the most common risk exposure sub-variables and adaptive processes.

The non-significant findings for positive student behaviors and school connectedness were surprising, prompting the need for further investigation into whether the findings were due to Type II error, data collection methodology, or actual nonimportance. Consequently, the Question 4 analyses could be replicated using a different data set or could be rerun using CDS teacher responses instead of parent and student responses. Finally, because the TAS is ongoing, I recommend a follow-up study after the PSID releases additional data to determine whether the current findings remain consistent in light of more complete degree completion information.

In summation, the current study provided a comprehensive analysis of academic success in relation to risk, income, and postsecondary degree completion by examining the academic trajectories of low-income students throughout their school careers. The findings had practical implication for identifying students at risk for academic decline and supporting the continued success of low-income students. However, the complex, pervasive, and persistent nature of the income achievement gap leaves many areas for further researchers to investigate.

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Vita

Linda K. Mayger
1714 White Acre Drive, Bethlehem, PA 18015
Phone: 484-851-3420 Email: lkm212@lehigh.edu

Education

University of Phoenix, Phoenix, AZ 2007
Master of Arts in Education, Curriculum and Instruction

Carroll University, Waukesha, WI 1988
Bachelor of Science in Elementary and Early Childhood Education

Publications

Mayger, L. K. & Zirkel, P. A. (2014) Principals' challenges to adverse employment actions: An empirical analysis of case law. *NASSP Bulletin,* DOI 10.1177/0192636514542872

Mayger, L. K. & Zirkel, P. A. (2014) Lessons learned from litigation: When principals challenge dismissals and other adverse employment actions, *Principal Leadership Magazine, (15)*3, 54-57.

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Mayger, L. (2007) Making the most of field trips, *Educational Leadership 64(summer).*

Certifications

PA- Principal, K-12
PA- K-6 Teacher Certification, Middle Level Math, Middle Level Science

Work Experience

Graduate Assistant, College of Education, 2013-2015
Lehigh University, Bethlehem, PA

Curriculum Specialist, 2009-2012
Seven Generations Charter School, Emmaus, PA

Middle School Math & Science Teacher, 2007-2009
St. Timothy's Preparatory School, Apple Valley, CA

Preschool Director, 1995-1997
Preschool Learning Center, Bowling Green, KY

Elementary Classroom Teacher, 1990-1995
Wauwatosa Public Schools, Wauwatosa, WI